

# A combined destination and route choice model for a bicycle sharing system

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**Abstract** This paper studies the supply variables that influence the destination and route choices of users of a bicycle sharing system in the Chilean city of Santiago. A combined trip demand logit model is developed whose explanatory variables represent attributes relating to the topology of the possible routes and other characteristics such as the presence of bikeways, bus service and controlled intersections. The data for the explanatory variables and system users were collected through field surveys of the routes and interviews conducted at the system stations. The results of the model show that proximity to stops on the Santiago Metro and the existence of bikeways are the main factors influencing destination and route choices. Also indicated by the model estimates are gender differences, a preference for tree-lined routes and an avoidance of routes with bus services. Finally, the outcomes reveal considerable potential for the integration of bicycle sharing systems with Metro transit.

**Keywords** Bicycle · Combined model · Route choice · Destination choice · Bikeway · Bicycle-Metro integration

## Introduction

This article attempts to determine how a set of explanatory variables relating to the supply of routes used by bicycle traffic (i.e., the route network) influences cyclist behaviour regarding route and destination choices. A solution approach is developed and then applied

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to the real case of the bicycle sharing (rental) system in Providencia, a municipality within the city of Greater Santiago in Chile.

The cyclists' demand functions are formulated as a combined destination and route choice model with a hierarchical logit structure (De Cea et al. 2008) in which the destination choice is in the upper nest and the route choice in the lower one (Ortúzar and Willumsen 2011). The model's parameters are estimated using maximum likelihood.

The results of the model show that in the system studied, destination choice is strongly influenced by Metro stop locations, indicating that a combined bicycle-Metro mode generates a strong synergy. Other interesting findings on the attributes of existing routes are that cyclists have marked preferences for those that are tree-lined or include bikeway segments while tending to avoid routes used by bus lines. Gender differences were also detected, with men using bikeways less than women.

Though these results are based on just one particular bicycle sharing system, we believe they provide valuable insights into future design features and innovations that could be incorporated into urban bicycle rental or loan systems generally. The ultimate goal is to enhance existing measures for encouraging the use of bicycles as a sustainable mode of transport that offers a series of advantages in terms of economics, health, the environment and quality of life (Ortúzar et al. 2000; Dill 2009; Pucher et al. 2010). In some urban areas, bicycles may even offer higher trip speeds than other means of transportation. They also have some disadvantages, however, such as the physical effort involved on longer trips, greater accident risk and exposure to the weather (Heinen et al. 2010). Improvements to the design of bicycle sharing systems are therefore a potential source of significant benefits.

A range of public policies have already been developed for promoting bicycles as transport, whether in isolation or integrated with public transit modes (Martens 2007; Pucher et al. 2010; Park et al. 2011). Many cities have opted to set up bicycle sharing systems as a user-friendly method of boosting connectivity with other modes, reducing car use and encouraging healthier lifestyles (Pucher et al. 2010; Dell'Olio et al. 2011; Lin and Yang 2011; Shaheen 2011).

Sharing systems are built around stations where registered (or paid-up) users can pick up and drop off bicycles. Payment methods, operational aspects and user information mechanisms differ from one system to the next. Currently, more than 160 cities have some sort of bicycle sharing scheme (Shaheen et al. 2012). In Greater Santiago, two of the city's 37 municipalities or districts (Providencia and Vitacura) have set up systems in the last few years. Two more (Ñuñoa and Las Condes) will soon have systems in place and the trend is expected to continue across the metropolitan area.

The success of these setups in terms of user numbers depends on a range of factors. One of the most important is their design characteristics, among which are the location of pickup/drop-off stations, existing routes and connectivity (Handy et al. 2010; Castillo-Manzano and Sánchez-Braza 2013). According to Lathia et al. (2012), there are three stakeholder groups to be considered: cyclists (the users), urban planners (the relevant authorities) and operators (the system concession holders). Good coordination and interaction between these groups will increase the chances of a system's success.

From an implementation standpoint, Lin and Yang (2011) find that an optimal bicycle sharing scheme design must take into account such considerations as user travel cost (in money and time), the construction cost of stations for bicycle pickup/drop-off and storage, and the cost of cycle facilities. With this in mind, the authors develop a non-linear programming model that determines the optimal choices for station location, bikeway network structure and user travel routes. However, they do not define the topological attributes or

characteristics of a set of existing routes, the approach that will be adopted in the present study.

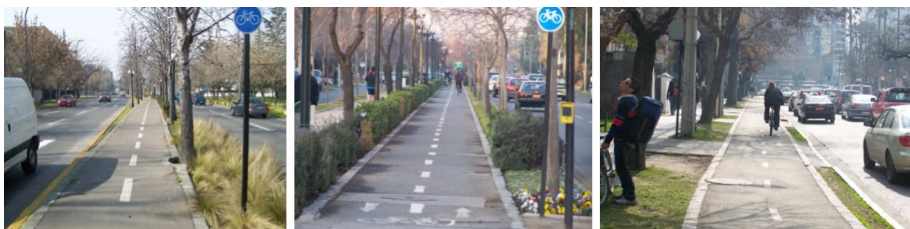
Various other published works aim to identify the most important variables impacting cyclists' route choices. Unlike the analysis we develop, however, most of these studies focus on bicycle owners who start their trips from home or the workplace, not users of a sharing system. As for the variables themselves, the two that stand out for their influence on route choice are route length and the existence of bikeways (Stinson and Bhat 2003; Hunt and Abraham 2007; Akar and Clifton 2009; Sener et al. 2009; Broach et al. 2012). The second factor is particularly valued by occasional users and women (DeGruyter 2003; Garrard et al. 2008; Winters and Teschke 2010; Hood et al. 2011). It has also been observed that users prefer routes with fewer controlled intersections (traffic lights, stop or give way/yield signs), fewer hills, lower motor vehicle traffic volumes and more attractive scenery (Parkin et al. 2008; Sener et al. 2009; Broach et al. 2012; Menghini et al. 2010; Winters et al. 2011).

The remainder of this article is organized into four sections. “**Bicycle sharing system**” section describes the bicycle sharing (rental) system that is the focus of our study and the local bikeway infrastructure; “**User data**” section reviews the data collected by our system user survey; “**Model and results**” section develops a combined destination and route choice model, introduces the set of possible explanatory variables, and presents and interprets the model parameter estimates; and finally, “**Conclusions**” section sets out our main conclusions and their implications for future bicycle sharing system designs.

## Bicycle sharing system

The Greater Santiago municipality of Providencia covers an area of 14 km<sup>2</sup> and is home to 125,000 residents, but due to its importance as a business, education and services centre it has a daytime population of about 800,000. It is also Santiago's pioneer in cycling infrastructure, having developed a plan for connecting up the district and its parks through a network that will eventually contain 45 kms of bikeways. About 12 kms of medium–high grade routes with good signage already exist, most of which consists of protected cycle lanes and greenways. Nevertheless, full connectivity between all of the municipality's trip generation and attraction points has not yet been achieved. Three examples of the district's bikeways are shown in Fig. 1.

Bikeway construction in Providencia has generally followed four main principles: (1) use the district's numerous thoroughfares with little or no bus service and low foot traffic to reduce conflicts between bicycles and pedestrians or bus stops; (2) criss-cross the district with equidistant bikeways so that cyclists can enter the network from any point; (3)

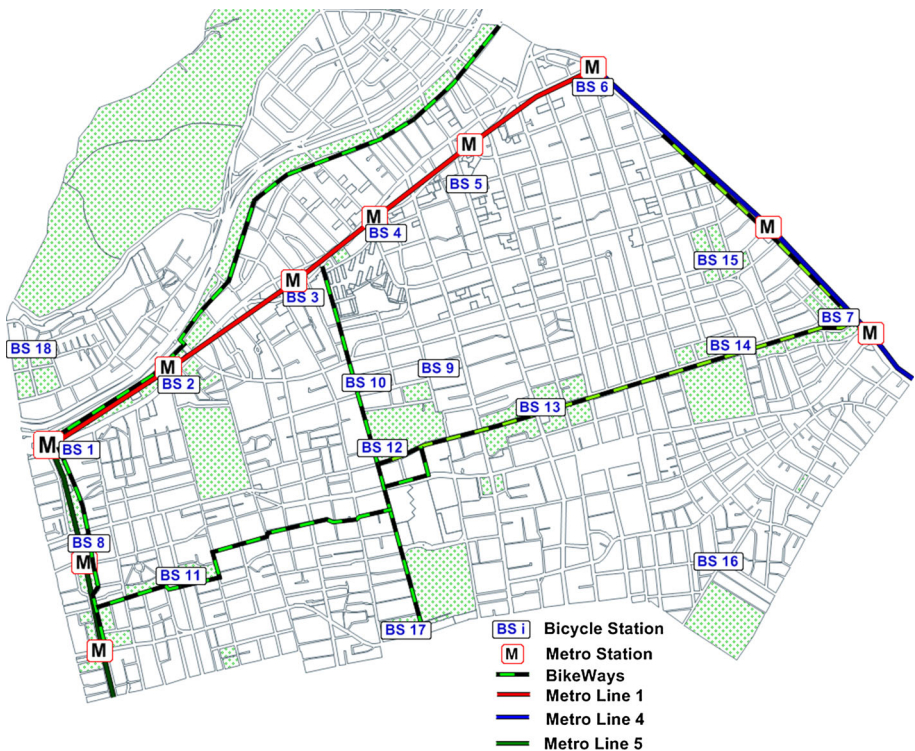


**Fig. 1** Bikeways in Providencia

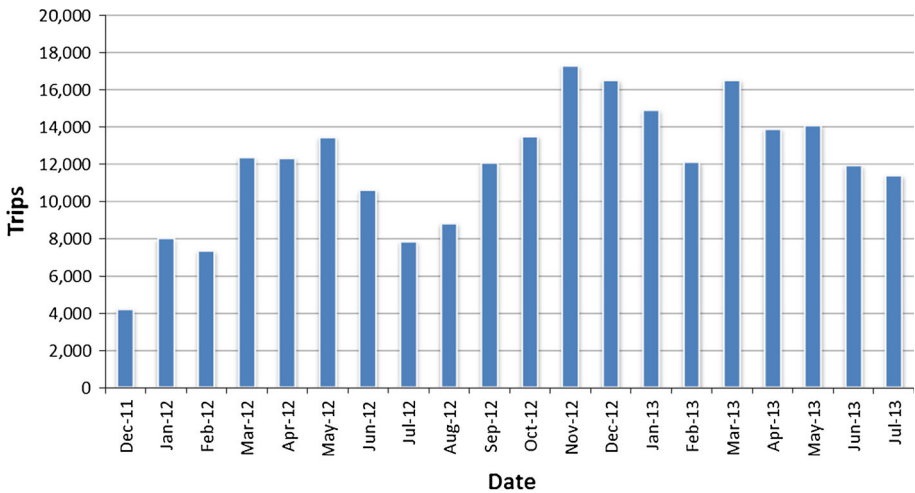
facilitate connections with neighbouring districts; and (4) connect with Metro stops to enable intermodal transfers (the municipality has 10 Metro stops on 3 lines).

To promote greater use of bicycle transport, Providencia set up Santiago's first bicycle sharing (rental) scheme in 2010. Operation of the scheme is outsourced to a concession-holder at a cost to the Municipality of about US\$40,000 per month. The system has 150 bicycles distributed strategically across 18 stations located around the district in highly-frequented locations near Metro stops, squares (i.e., "plazas"), and sports and cultural centres. Each station has 20 bicycle docks. Operating hours are 7:30 am–8:30 pm, Monday through Saturday. The bicycles each have a code and can be picked up at any station subject to availability up to 30 min before closing time upon showing proof of registration to the station attendant. The rental period is 1 hour but can be renewed for an additional 60 min. Three trucks reposition bicycles throughout the day from stations where drop-offs have built up surpluses to stations where pickups have depleted their numbers, thus maintaining a balanced distribution. A map of the municipality indicating the station locations as well as the existing bikeways and the Metro lines and stops is shown in Fig. 2.

Persons wishing to use the system must first register either at any of the stations, through the system's web page or at the concession-holder's offices. The registration fee is US\$4 a month or US\$30 a year. As of July 2013 there were about 3,000 registered users, 2,500 of whom paid on a monthly basis. The trend in monthly trip demand for the system's bicycles between December 2011 and July 2013 is graphed in Fig. 3. For purposes of these statistics, each pickup/drop-off pair was counted as a single trip. The growing awareness



**Fig. 2** Bicycle stations and Metro lines in Providencia



**Fig. 3** Users' monthly trip demand

and acceptance of the system is reflected in the monthly trip numbers, which have increased from 4,200 in December 2011 to an average of more than 17,000 in November–December 2012. Note that the figures tend to fall in June and July as these are mid-winter months in the Southern Hemisphere.

The number of trips generated and attracted by each of the 18 stations in the system during March 2013 is given in Table 1. Also shown for each station are its location (defined in terms of a nearby Metro stop line, park or other place of interest) and the total distance travelled by users on bicycle trips originating there. According to these data, the average trip length for the approximately 16,500 trips taken in the indicated month was 1.9 km and the origin or destination for 51 % of the trips was a station near a Metro stop. This suggests the bicycles were used primarily as a mode of transport for either getting to the Metro or to a final destination.

## User data

Two types of data were collected for the purpose of estimating our proposed trip demand model, introduced in the next section. The first type consisted of information on the explanatory variables relating to supply and was gathered through a detailed field survey of the spatial attributes of the various route alternatives used by cyclists in Providencia. These data will be presented below along with the model.

The second type of data related to certain characteristics of the cyclists who used the bicycle rental system. Users were surveyed at the system stations as they picked up or dropped off bicycles, for the most part during the morning or afternoon peak hours (8 am–10 am and 5:30 pm–7:30 pm, respectively) during November 2012 and March 2013. Some of them chose to send in their responses later by e-mail.

The user survey design was a simple random sample and the questions were divided into three parts. The first part collected information on individual user demographics such as sex, age, residence (in or outside of Providencia), marital status and occupation. The

**Table 1** Trips by users, March 2013

Bicycle station	Location	Number of trips generated	Number of trips attracted	Average trip length (metres)
1. Plaza Baquedano	Metro line 1 and 5	1,174	804	2,298
2. Salvador	Metro line 1/Park	571	512	2,029
3. Manuel Montt	Metro line 1	1,113	1,112	1,618
4. Pedro De Valdivia	Metro line 1	1,948	2,100	1,594
5. Lota	Metro line 1	1,484	1,656	1,327
6. Hernando de Aguirre	Metro line 1 and 4	1,240	1,526	2,416
7. Parque Augusto Errazuriz	Metro line 4/Park	298	384	2,684
8. Parque Bustamante	Metro line 5	1,039	779	1,864
9. Providencia	Town Hall	1,364	1,585	1,286
10. Federico Froebel	University/Park	991	901	1,793
11. Marín	Park	709	563	1,827
12. Plaza Inés De Suarez	Park	611	565	1,847
13. Pocuro	Park	1,669	1,820	1,885
14. Plaza Rio Janeiro	Park	578	666	2,101
15. Plaza Las Lilas	Park	415	459	2,007
16. Plaza Chile España	Park	465	298	3,588
17. Plaza Santa Isabel	Park	617	690	2,676
18. Plaza Cardenal	Park	222	88	2,327
Total		16,508	16,508	1,905

second part inquired into the details of the user's trip: origin, destination, route used, trip duration, reason for trip and frequency of trip (i.e., how often the user made the same trip in a week). Finally, the third part asked about the main reason for using the system, the use of bikeways and the transport mode alternatives available to the user.

Selected results from the survey on user demographics are summarized in Table 2. As can be seen, 63 % of the users were male, and as with the female users, most of them were between the ages of 20 and 39. Also, only 57 % of respondents lived in Providencia whereas 43 % resided in neighbouring districts, a reflection of our earlier observation regarding Providencia's high concentration of offices, businesses, educational institutions and other services.

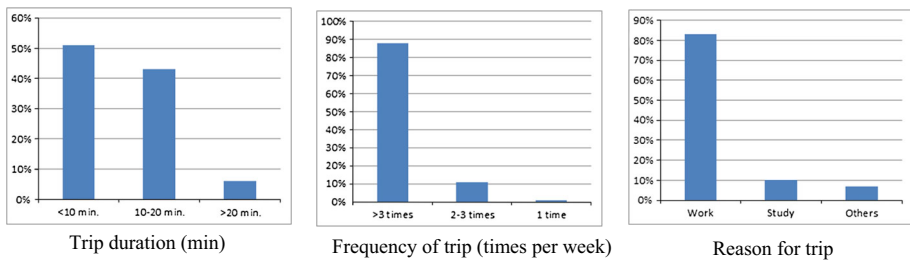
Survey data on user trips are illustrated by the pie charts in Fig. 4. They indicate that for 51 % of respondents, trip duration was less than 10 min while for 43 % it was 11–20 min. In addition, 88 % of users said they used the system more than 3 times a week and 83 % of them did so as part of their commute to work.

When system users were asked for their opinions on the user fees, 95 % said they did not consider the charges to be a significant factor. The data on user motives are depicted in Fig. 5. As can be observed, 33 % of respondents declared they used the bicycle sharing system because it was a speedy way of getting around while 22 % saw it as an opportunity to practise a sport. Only 8 % cited economic reasons.

As for bikeways, 71 % of respondents said they used them. Among those who did not, the overwhelming majority cited the absence of any that were convenient for their route while relatively small numbers referred either to their frequent use by pedestrians, the fact that the trip would take longer or some other reason (see Fig. 6).

**Table 2** Demographic characteristics of users

Sex	Age	Non-Resident of Providencia (%)	Resident of Providencia (%)	Total (%)
Female	<20	0	0	0
	20–29	4	9	13
	30–39	5	13	18
	40–49	1	1	2
	50–59	1	3	4
	>=60	0	0	0
	Total	10	27	37
Male	<20	1	0	1
	20–29	10	9	19
	30–39	13	13	26
	40–49	7	5	12
	50–59	1	3	4
	>=60	0	1	1
	Total	33	30	63

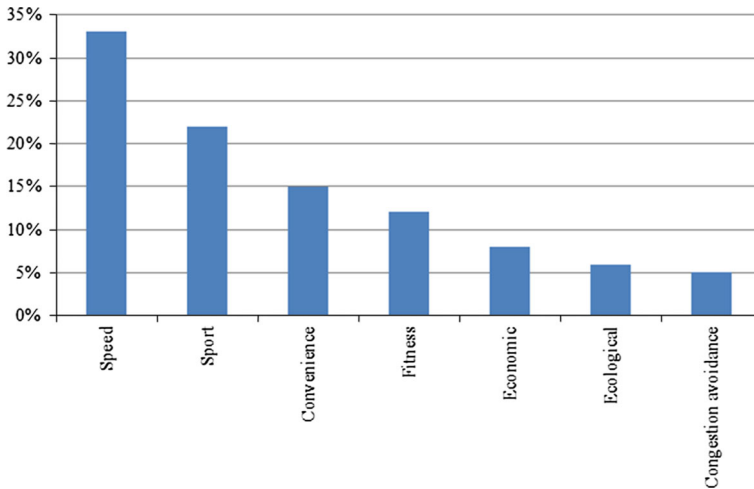


**Fig. 4** Characteristics of user trips

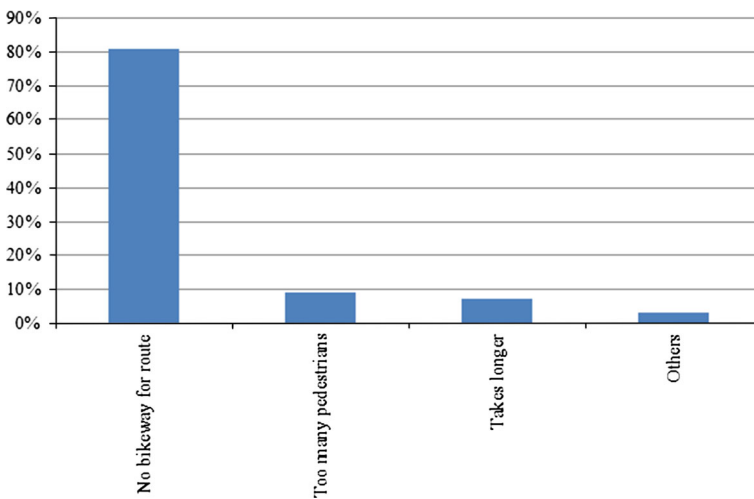
Finally, the survey data on users’ transport mode alternatives are presented in Fig. 7. Although 55 % of respondents owned a car, only 4 % said they would use it for the same trip. Their preferences for other alternatives to cycling were walking (49 %), the Metro (21 %) and the bus (17 %). Such responses no doubt reflect the fact that trip lengths were short (consistent with the short trip durations indicated in Fig. 4), which accounted in particular for the popularity of the walking option.

**Model and results**

We now set out our combined trip demand logit model (Abrahamsson and Lundqvist 1999; Florian et al. 2002; Boyce and Bar-Gera 2003; Ham et al. 2005; García and Marín 2005; De Cea et al. 2008; Donoso et al. 2011; De Grange et al. 2013) for determining the impact of certain variables on the destination and route choices of cyclists using the Providencia bicycle sharing system.



**Fig. 5** Motives for using bicycle sharing system and significance of user fees



**Fig. 6** Reason for not using bikeways

The basic hierarchical structure of the proposed formulation is shown in Fig. 8. Given an origin, users first elect any one of the  $n$  other stations as their destination and then choose between  $r_m$  possible routes. The model can be specified using random utility theory in analogous fashion to the combined trip distribution and mode share models developed by Anas (1981) and Ortúzar and Willumsen (2011). The latter article interprets the parameters in a random utility model as scale factors, but they can also be considered as the weighting factors for the hierarchical choice decisions (De Cea et al. 2008). On this interpretation,  $\eta$  and  $\lambda$  indicate which of the two decisions dominates, that is, whether a route is decided given a chosen destination or a destination is decided given a chosen route. In our specification it was assumed the destination is decided first and then the route given



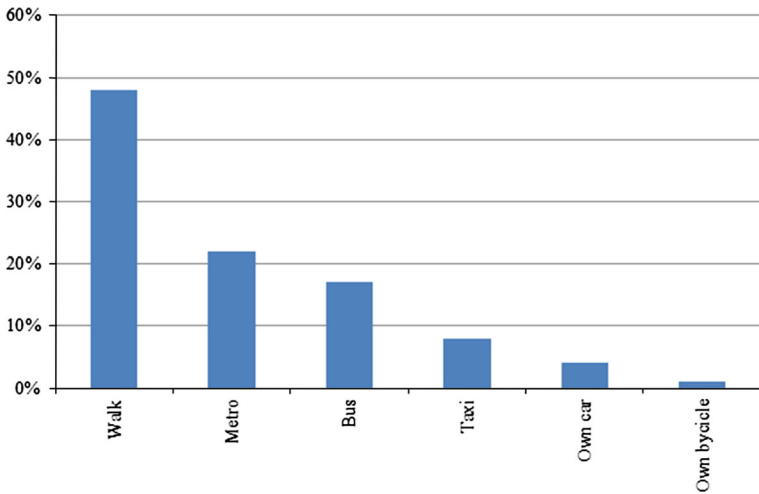


Fig. 7 Alternative transport modes available to users

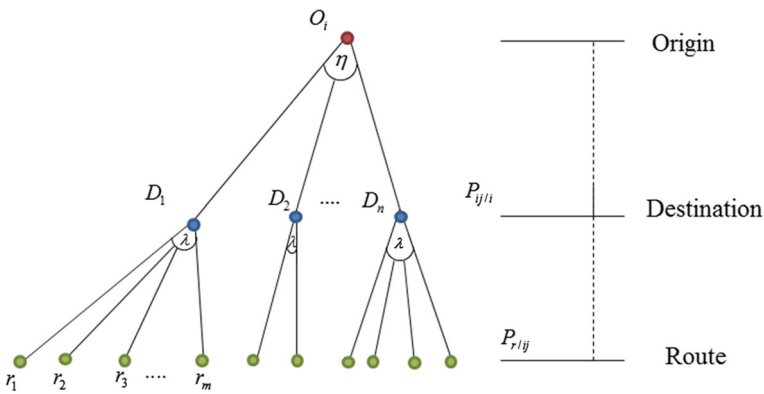


Fig. 8 Hierarchical tree structure of the model

that destination. This assumption would be confirmed if  $\eta/\lambda < 1$ , which was found to be the case once the parameters were calibrated.

It then follows that the probability of choosing route  $r$  to travel between origin and destination pair  $ij$  is given by

$$P_{ij}^r = P_{ij/i} P_{r/ij} \tag{1}$$

where  $P_{ij/i}$  is the probability of choosing destination zone  $j$  given that the trip originated in zone  $i$  (destination choice model) and  $P_{r/ij}$  the probability of choosing route  $r$  within the  $ij$  choice (route choice model).

The route choice model is therefore stochastic. It also explicitly incorporates the correlation between the alternative routes by including a path size attribute in the utility function (Ben-Akiva and Bierlaire 1999) to correct for the existence of routes that have

overlapping links, while maintaining a multinomial logit model structure Thus,  $P_{r/ij}$  is formulated as

$$P_{r/ij} = \frac{e^{V_{ij}^r + \psi \cdot \ln PS_{ij}^r}}{\sum_{r \in R^{ij}} e^{V_{ij}^r + \psi \cdot \ln PS_{ij}^r}} \tag{2}$$

where  $V_{ij}^r = \sum_k \beta^k x_{ij}^{kr}$  is a linear combination of explanatory variables representing the attributes of each available route for O–D pair  $ij$ , and  $\beta^k$  are the corresponding parameters. The  $PS_{ij}^r$  term is the path size correction factor for routes with overlapping links and  $\psi$  is a calibration parameter. The functional form proposed for the path size term (Ben-Akiva and Bierlaire 1999) is

$$PS_{ij}^r = \sum_{a \in r} \left( \frac{l_a}{L_r} \cdot \frac{1}{\sum_{r \in R^{ij}} \delta_{ar}} \right) \tag{3}$$

where  $l_a$  is the length of a link  $a$ ,  $L_r$  is the length of route  $r$ ,  $\delta_{ar}$  is equal to 1 if link  $a$  belongs to route  $r$  and 0 otherwise, and finally,  $R^{ij}$  is the set of possible routes connecting pair  $ij$ .

The path size correction is applied to the routes as follows. A route that has no links overlapping those of any other route needs no correction and therefore  $PS_{ij}^r = 1$ . At the other extreme, if there are  $J$  routes that completely duplicate one other (i.e., their respective links totally overlap), then  $PS_{ij}^r = 1/J$  for each route. Finally, if a route partially overlaps another route, the size of the  $PS_{ij}^r$  factor depends on the lengths of the overlapping links. Each such link is appropriately weighted according to some criterion, which in the present case is the proportion of the route length the link accounts for. Other specifications of the correction factor  $PS_{ij}^r$  may be found in Bovy et al. (2008).

For each of the 157 O–D different pairs observed in the survey, the choice set of route alternatives ( $R^{ij}$ ) connecting it is defined as the union of two sets of routes generated using different criteria (excluding routes common to both). The first set includes all the different routes to have been chosen by users for each pair in the system (Raveau et al. 2011) while the second set consists of the four shortest routes for each of the 157 pairs as determined by the K-shortest path algorithm (Van der Zijpp and Fiorenzo Catalano 2005; Prato 2012), assuming all route links in the network are bidirectional. Upon generating the choice set, the average number of alternatives for each O–D pair was found to be 4.2. All trips with the same origin and destination stations were eliminated from the collected data.

The destination choice model, on the other hand, has the following functional form:

$$P_{ij/i} = \frac{e^{\phi L_{ij} + Z_j}}{\sum_j e^{\phi L_{ij} + Z_j}} \tag{4}$$

where  $L_{ij} = -\ln \sum_{r \in R^{ij}} e^{V_{ij}^r + \psi \cdot \ln PS_{ij}^r}$ ,  $\phi = \left(\frac{\eta}{\lambda}\right)$  and  $Z_j = \sum_m \alpha_m x_j^m$  is a linear combination of  $m$  explanatory variables representing the attributes of destination  $j$  and its corresponding parameters  $\alpha_m$ . Thus,  $L_m$  can be interpreted simply as the expected maximum utility (EMU) of route  $ij$ . Note that in this model, the choice set for each origin considered only the destinations observed in the survey, which numbered approximately 8.

The combined destination and route choice model is then given by

$$P_{ij}^r = \frac{e^{\phi L_{ij} + Z_j}}{\sum_j e^{\phi L_{ij} + Z_j}} \frac{e^{V_{ij}^r + \psi \cdot \ln PS_{ij}^r}}{\sum_{r \in R_{ij}} e^{V_{ij}^r + \psi \cdot \ln PS_{ij}^r}} \tag{5}$$

As explained above, in addition to user characteristics the spatial attributes of the various route alternatives were also surveyed. The relevant data, gathered through field visits and Google street view (<https://www.google.cl/maps>), were employed to determine and quantify the main topological factors influencing user route choice (Raveau et al. 2011). The corresponding variables are displayed in Table 3 together with two variables from the user survey (Age, Freq), a series of dummy variables representing specific user and route choice characteristics, and, for the non-binaries, their respective means and standard deviations.

These variables constitute the set of possible explanatory variables for the combined model. Several subsets of these variables were estimated. The parameter coefficients for

**Table 3** Explanatory variables

Variable	Description	Mean	SD
Length	Route length (m)	1,828.27	813.96
Bikeway	Proportion of route with any type of bikeway	0.31	0.28
Nlights	Number of traffic lights along route	4.45	3.05
Nsignals	Number of stop or give way/yield signs along route	0.48	1.41
Width	Width of pavements/sidewalks along route (m)	2.60	0.94
Nlane	Average number of motor vehicle lanes along route (both directions)	2.45	0.54
Ntree	Number of trees per 50 metres of route	1.45	0.41
Tpub	Proportion of route served by public transit	0.48	0.35
PS	Path size measure	0.32	0.26
Freq	Frequency of trip (no. of times per week)	3.07	1.25
Age	Age of user (years)	36.67	10.33
Tree	Dummy variable equal to 1 if there is at least 1 tree per 50 metres along 60 % of route*	59.1 %	n/a
SexBway	Result of multiplying value of Bikeway variable by value of dummy variable equal to 1 if user is male**	63.1 %	n/a
DFreqBway	Result of multiplying value of Bikeway variable by value of dummy variable equal to 1 if user makes trip more than 3 times a week**	88.3 %	n/a
YoungLength	Result of multiplying value of Length variable by value of dummy variable equal to 1 if user is under 35 years of age**	61.4 %	n/a
Office Services	Area occupied by offices within a 700-metre radius of a Metro station	94,438	42,647
	Area occupied by service sector businesses within a 700-metre radius of a Metro station	44,088	39,388
Metro	Dummy variable equal to 1 if there is a Metro stop less than 700 metres from destination bicycle station**	53.7 %	n/a
MetroL1	Dummy variable equal to 1 if there is a Line 1 Metro stop within a 700-metre radius of destination bicycle station**	46.7 %	n/a
MetroL5	Dummy variable equal to 1 if there is a Line 5 Metro stop within a 700-metre radius of destination bicycle station**	9.6 %	n/a

\* Figure for mean is the average over all alternative routes and all users in the sample

\*\* Figure for mean is the average value of the dummy variable over all users before multiplying by the indicated continuous variable

**Table 4** “Best” model estimation results

Parameter (by variable name)	Estimation results	
	Coefficient	<i>t</i> test value
$\beta_{\text{Length}}$	-1.67	-2.34
$\beta_{\text{Bikeway}}$	2.92	2.41
$\beta_{\text{SexBway}}$	-1.55	-1.74
$\beta_{\text{Tree}}$	1.08	1.97
$\beta_{\text{Tpub}}$	-0.82	-2.16
$\psi_{\text{PS}}$	2.39	2.47
$\alpha_{\text{Metro}}$	0.14	4.31
$\alpha_{\text{Office}}$	0.62	7.97
$\alpha_{\text{Services}}$	0.15	5.78
$\phi$	0.19	6.08
No. of observations	304	
$\hat{\rho}^2$	0.324	
Log-likelihood	-109.01	
Null Log-likelihood	-176.14	

what we considered to be the “best” subset are given in Table 4 together with their *t* test values; the results for two other subsets are shown in Appendix Table 5. The estimation itself was by maximum likelihood using the GAUSS 7.0 software program.

All of the parameter values had the expected sign and were statistically significant at the 95 % confidence level except for the value of  $\beta_{\text{SexBway}}$ , which was significant at the 91.8 % level. The negative sign for the route length parameter confirms that the users were rational in choosing shorter routes. An increase of 100 metres in the trip distance of a given route with all other routes held constant results in a drop of 18 % in the probability that route will be chosen.

These results also lead to the conclusion that bikeways induce greater user flows given that the associated parameter value ( $\beta_{\text{Bikeway}} = 2.92$ ) is positive and statistically strong. Thus, users prefer routes with longer bikeway segments. Indeed, this attribute has the greatest statistical significance of any characteristic relating to available routes except destination attributes. An increase of 1 % in the bikeway portion of a route leads to a 3 % rise in the probability users will choose it. Also evident from the results is that women value the existence of bikeways 4 times more than men do in their route choices more than men in their route choices.

The parameters for the presence of trees ( $\beta_{\text{Tree}}$ ) and public transit service ( $\beta_{\text{Tpub}}$ ), as well as being statistically significant, are signed positive and negative respectively. This suggests that users prefer to travel along routes that are tree-lined (making the trip more scenic) and served by fewer buses (making the route safer and quieter). It follows that potential routes can be made more attractive to cyclists by placing more trees along them and locating bikeways on streets not served by surface transit.

As regards destination variables, the presence of a nearby Metro stop clearly influenced positively the choice of a drop-off station, corroborating the well-established assumption that the bicycle sharing system was being used as an alternative for connecting to the Metro. Similarly, stations with high concentrations of offices and services in the immediate vicinity (measured in terms of area they occupy within a 700-metre radius) also attracted more bicycle trips.

The results (including those of the other models presented in the Appendix Table 5) showed no evidence that either the number of controlled intersections along a route, the

width of the pavements/sidewalks or the number of lanes significantly influenced the choice of one route over another.

Finally, if the model is used for forecasting, the choice set should be defined exogenously. An alternative is to use the K-shortest path algorithm criteria (Van der Zijpp and Fiorenzo Catalano 2005; Prato 2012). Additional criteria are presented and analyzed in Bekhor et al. (2006), where different criteria for estimating a Path Size Logit Model in large networks are compared; these criteria are exogenous and allow use the model for forecasting.

## Conclusions

This study developed a combined trip demand logit model for determining the supply attributes that most influence the destination and route choices of users of a bicycle sharing (rental) system in a single district within the Chilean city of Santiago. The parameters of the model were estimated using maximum likelihood.

The data collected for the study found that most persons who used the bicycle sharing system did so as a way of connecting to the Santiago Metro for commuting to work, and used the system more than 3 times a week. Most trips were short (less than 20 min). Users did not necessarily live in the district and the majority did not consider the rental fees to be significant factor.

The results of the demand model indicated that for the system studied, choice of destination was strongly determined by the socioeconomic characteristics of the immediate vicinity of the system's pickup/drop-off stations as well as the nearby presence of a Metro stop. The latter finding reveals the existence of a marked synergy between the two modes of transport. This is a particularly valuable conclusion as it implies that the integration of the two modes should be an important design consideration for future loan- or rental-based bicycle sharing systems in cities with a Metro.

Another interesting result relating to the attributes of existing bicycle routes was that cyclists strongly preferred those that include bikeway segments, suggesting users might see them as safer options. This conclusion is supported by the additional finding that cyclists tended to avoid routes served by buses.

It was also found that users of the bicycle sharing system preferred tree-lined routes, probably due to their scenic value though it is also possible the presence of the trees created a sensation of greater safety. Finally, the model results confirmed a statistically significant gender difference in that men tended to use bikeways less than women.

Taken together, these various findings provide a number of insights into design considerations for both bicycle sharing systems and cycle paths, and point to certain design and operating attributes that would induce greater use of the system, thus strengthening the effectiveness of public policies aimed at offering more sustainable transport alternatives in urban areas.

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## Appendix

The parameter values for two additional models containing different subsets of the set of possible explanatory variables are presented here together with the values for the “best” set discussed in the main text (See Table 5).

**Table 5** Estimation results: comparison of “Best” and other models

Parameter	Model 1		Model 2		Model 3		Model 4		Model 5	
	Coefficient	t test value	Coefficient	t test value	Coefficient	t test value	Coefficient	t test value	Coefficient	t test value
$\beta_{Nights}$	-0.05	-0.47								
$\beta_{Nsignals}$	-0.15	-0.32								
$\beta_{Width}$	0.11	0.55								
$\beta_{Nlane}$	-0.20	-0.71								
$\beta_{Tree}$	1.08	1.98**	1.12	1.99**	1.14	2.01**	1.16	2.02**	1.09	1.98**
$\beta_{Bikeway}$	2.40	4.21***	2.96	2.49**	2.95	2.51**	2.91	2.89***	2.70	2.61***
$\beta_{SexBway}$			-1.52	-1.70*	-1.53	-1.73*	-1.56	-1.74*	-1.48	-1.67*
$\beta_{DFreqBway}$			-0.47	-0.56						
$\beta_{Length}$	-1.62	-2.24**	-1.61	-2.23**	-1.61	-2.22**	-1.60	-2.21**	-1.59	-2.13**
$\beta_{YoungLength}$			0.14	0.29						
$\beta_{Tpub}$	-0.82	-2.09**	-0.84	-2.17**	-0.84	-2.18**	-1.03	-1.87*		
$\beta_{TpubBikeway}$							0.24	0.85		
$\beta_{Tpub\_2}$									-1.11	-1.92*
$\psi_{PS}$	2.45	2.53**	2.46	2.55**	2.46	2.56**	2.43	2.53**	2.38	2.47**
$\alpha_{Metro}$	0.37	3.58***	0.38	3.59***	0.37	3.61***	0.14	4.25***	0.14	4.22***
$\alpha_{MetroL1}$	0.45	4.53***	0.46	4.58***	0.46	4.55***				
$\alpha_{MetroL5}$	0.15	5.62***	0.16	5.61***	0.16	5.63***				
$\alpha_{Office}$							0.61	7.94***	0.62	7.85***
$\alpha_{Services}$							0.16	5.57***	0.15	5.86***
$\phi$	0.19	6.85***	0.18	6.72***	0.18	6.76***	0.19	6.29***	0.19	6.33***
No of observations	304		304		304		304		304	
$\rho^2$	0.295		0.311		0.313		0.315		0.318	
Log-likelihood	-111.12		-110.94		-111.01		-109.57		-110.07	

**Table 5** continued

Parameter	Model 1		Model 2		Model 3		Model 4		Model 5	
	Coefficient	t test value	Coefficient	t test value	Coefficient	t test value	Coefficient	t test value	Coefficient	t test value
Null-likelihood	-176.14		-176.14		-176.14		-176.14		176.14	

TpubBikeway: Result of multiplying values for TPub and Bikeway variables

Tpub\_2: Proportion of route served by public transit for routes with no bikeway segments

\* Indicates significance at the 90 % confidence level, \*\* indicates significance at the 95 % level; \*\*\* indicates significance at the 99 % level

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