Transportation Research Part A 46 (2012) 1730–1740

Contents lists available at SciVerse ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

Where do cyclists ride? A route choice model developed with revealed preference GPS data

Joseph Broach [a], Jennifer Dill [a,*], John Gliebe [b]

[a] Nohad A. Toulan School of Urban Studies and Planning, Portland State University, PO Box 751, Portland, OR 97207-0751, United States
[b] Resource Systems Group, Inc., 55 Railroad Row, White River Junction, VT 05001, United States

ARTICLE INFO

Article history:
Received 18 August 2011
Received in revised form 11 June 2012
Accepted 14 July 2012

Keywords:
Bicycling
Route choice
Bicycle infrastructure
Bicycle lanes
Revealed preference

ABSTRACT

To better understand bicyclists' preferences for facility types, GPS units were used to observe the behavior of 164 cyclists in Portland, Oregon, USA for several days each. Trip purpose and several other trip-level variables recorded by the cyclists, and the resulting trips were coded to a highly detailed bicycle network. The authors used the 1449 non-exercise, utilitarian trips to estimate a bicycle route choice model. The model used a choice set generation algorithm based on multiple permutations of path attributes and was formulated to account for overlapping route alternatives. The findings suggest that cyclists are sensitive to the effects of distance, turn frequency, slope, intersection control (e.g. presence or absence of traffic signals), and traffic volumes. In addition, cyclists appear to place relatively high value on off-street bike paths, enhanced neighborhood bikeways with traffic calming features (aka "bicycle boulevards"), and bridge facilities. Bike lanes more or less exactly offset the negative effects of adjacent traffic, but were no more or less attractive than a basic low traffic volume street. Finally, route preferences differ between commute and other utilitarian trips; cyclists were more sensitive to distance and less sensitive to other infrastructure characteristics for commute trips.

1. Introduction

Non-motorized travel options have been largely ignored in regional transportation planning and travel demand modeling in the US, where decisions on more resource-intensive investments in highway and transit facilities have been of primary concern. Recently, however, policy maker interest in sustainable transportation and healthier lifestyles has shifted some of the focus to bicycling and walking and the extent to which the urban travel environment supports these modes. This shift raises questions about what types of infrastructure and policies may increase levels of bicycling for transportation and by how much, though the evidence answering these questions is scarce (Pucher et al., 2010; Yang et al., 2010).

Cities that are investing in bicycle infrastructure are faced with decisions of where to invest and what type of facility to install, e.g. bike lanes or separate paths. Several aggregate-level studies have found positive correlations between bike lanes and overall levels of bicycling (Dill and Carr, 2003; Nelson and Allen, 1997; Parkin et al., 2007; Pucher and Buehler, 2005), but studies at the individual level have been far less conclusive (Cervero and Duncan, 2003; de Geus et al., 2008; Dill and Voros, 2007; Krizek, 2006; Vernez-Moudon et al., 2005). Some individual-level revealed preference studies have found a correlation between cycling and proximity to separated paths (Vernez-Moudon et al., 2005) or that cyclists go out of their way to use paths, indicating their value (Howard and Burns, 2001; Krizek et al., 2007), though other studies do not (Aultman-Hall et al., 1998; Krizek, 2006). Studies that ask people their preferences often find preferences for more separated facilities (e.g. paths

* Corresponding author. Tel.: +1 503 725 5173; fax: +1 503 725 8770.
E-mail addresses: jbroach@pdx.edu (J. Broach), jdill@pdx.edu (J. Dill), john.gliebe@rsginc.com (J. Gliebe).

0965-8564/$ - see front matter
http://dx.doi.org/10.1016/j.tra.2012.07.005

or cycletracks) over striped lanes or no facilities (Bohle, 2000; Emond et al., 2009; Jensen, 2007; Rose and Marfurt, 2007; Shafizadeh and Niemeier, 1997; Winters and Teschke, 2010).

There is some evidence that facility preferences vary by individual characteristics. Studies asking individual preferences have found that experienced cyclists prefer lanes over separate paths (Akar and Clifton, 2009; Antonakos, 1994; Bureau of Transportation Statistics, 2004; Hunt and Abraham, 2007; Stinson and Bhat, 2003; Tilahun et al., 2007) or that they have a weak or no preference for lanes at all (Sener et al., 2009; Taylor and Mahmassani, 1996). There is some evidence that women and less-experienced cyclists have a higher preference for more separated facilities and avoiding high traffic volumes or speeds (Garrard et al., 2008; Jackson and Ruehr, 1998; Winters and Teschke, 2010). However, much of the evidence about relative preferences (e.g. paths vs. lanes) is based upon stated preference survey techniques, rather than revealed preference data, and sometimes ignores the realities of what networks are available for any particular trip.

The lack of good data linking types of bicycle infrastructure to cycling behavior is one reason the primary tool transportation agencies use to evaluate investment options – a regional travel demand model – typically does not address bicycling well, if at all. To our knowledge, many models employed in North America do not include bicycling in all steps of the process, e.g. trip generation, mode choice, route choice, *and* network assignment. Non-motorized trips are often combined (walking and bicycling) and left out after the mode choice step. When cycling is included, a typical practice has been to assume that cyclists choose the minimum-distance path between origins and destinations using a fixed travel speed (Larsen and El-Geneidy, 2011). This approach ignores network features, such as slope, traffic volumes, and the presence of on and off-street bikeways, and does not differentiate between bicycle trip purposes.

This paper presents findings from a bicyclist route choice model that reveals the relative attractiveness of different types of facilities, as well as the effect of traffic control devices (e.g. stop signs and signals) and topography on route choice. The model was developed using global positioning system (GPS) data collected from 164 bicyclists over the course of several days in Portland, OR. We only analyze data from utilitarian trips, such as commuting, shopping, eating out and errands, as route choice decisions are different for non-utilitarian (or "exercise") bicycling. In the remainder of this paper we review the existing literature on bicycle route choice modeling; describe the person, GPS, and network data used in model development; briefly explain important modeling assumptions regarding choice set generation and overlapping alternatives; and present the model specification and estimation results. Finally, we conclude with an assessment of what we believe to be the important modeling and policy implications of this research and suggest possible avenues for further development of the model.

2. Methods

2.1. Previous research on bicycle route choice modeling

The methods used in bicycle route choice research have evolved over time. Much of the early work focused on only a few variables and did not employ multivariate analysis methods (Sener et al., 2009). The dominant data collection method has been stated preference (SP) surveys. At their simplest, SP surveys ask respondents to rank or rate their preferences for different types of facilities. More sophisticated SP surveys give side-by-side route options from which to choose; the options are designed to force the respondent to trade off presumably positive features, such as a separated bike path, with longer travel times. Several studies have used these techniques applied to bicycle route choice (Hunt and Abraham, 2007; Krizek, 2006; Sener et al., 2009; Stinson and Bhat, 2003).

Stated preference methods are appealing for several reasons. Data collection is often easier or less expensive, compared with asking respondents to recall actual routes or equip participants with GPS devices. Detailed travel network data are unnecessary. There is no need to solve the formidable problem of generating alternative routes on a real network, though devising revealing pairs of route options can be challenging. Model specification and estimation are also simpler due to the "clean" data and limited number of alternatives. From a policy perspective, SP surveys allow researchers to test rare or nonexistent options that are not possible with revealed preference data. There are drawbacks to stated preference data for cyclist route choice. It is difficult to know how well a participant can map these textual or pictorial representations to her preferences for real facilities. Many salient features of a route are sure to be missing on a piece of paper or computer screen. Also, although the choice set is in a sense controlled, it seems likely that respondents have in mind their own usual routes as points of comparison. Landis et al. (1998) conducted an interesting variation on the typical stated preference method. Participants actually rode predefined alternative routes before evaluating each. There still may be a problem assuming cyclists can evaluate an unknown route in the same way they do a familiar one, but the technique does promise greater realism. Strategic bias is a possibility if participants think responses might influence policy outcomes. None of this is to say stated preference studies are not useful and the results valid, only that their advantages in execution involve tradeoffs.

A handful of revealed preference studies have been undertaken on this topic, but in general they are limited studies that do not estimate a full route choice model. Most commonly, cyclists have been asked to recall routes. The routes are then compared with pre-selected routes based on shortest paths or other definitions of optimal paths (Aultman-Hall et al., 1998; Howard and Burns, 2001; Larsen and El-Geneidy, 2011; Winters et al., 2010). For example, Larsen and El-Geneidy (2011) collected route data on common bike trips from cyclists in Montreal, Canada and compared them to the shortest path. These studies have the advantage of using actual routes and network data. The ability of cyclists to accurately recall routes is a question, but it may be quite accurate for habitual routes like commute trips. The larger shortcoming of these studies is the limited choice sets and lack of compensatory choice models. An exception is the recent work of Menghini et al. (2010) that developed a cyclist route choice model using GPS data from Zurich, Switzerland. Bicycle mode had to be imputed from the data, and no person or trip purpose characteristics were available, although the authors were able to construct some person variables from the GPS data (e.g. average speed). Network data were limited to distance, slope, traffic lights, and a variable for designated bike routes.

2.2. This study's data and methods

This research relies on GPS data collected from March through November 2007, by 164 bicyclists recruited using a variety of non-random methods from throughout the Portland, OR metropolitan area (for more information on sampling, see Dill, 2009; Dill and Gliebe, 2008). Each participant completed a survey with questions about demographics, bicycle travel patterns, and attitudes prior to screening for participation in the GPS data collection. The participants were primarily regular cyclists who reported riding more than 1 day per week, year-round. Although regular cyclists are more likely to be male (80% according to the phone survey), we oversampled women, resulting in a GPS sample composed of 44% females. Among all respondents, 89% were between the ages of 25 and 64. Compared with a random phone survey of adults about bicycling in the region (Dill and Voros, 2007), the GPS participants were slightly older, were more likely to have a college degree, had higher incomes, and were more likely to have full-time jobs than other regular cyclists. They were also more likely to live in a two-person household. Only 7% lived in a household without a car. This was by design. The sample purposely favored cyclists who had an option to drive.

Participants were outfitted with small hand-held GPS devices, which they clipped onto their bicycles. The devices were programmed for the participant to enter both weather and trip purpose at the beginning of each trip and to indicate whether the bicycle was being taken on transit or another motor vehicle. The device recorded the location every 3 s. Once returned, the data were downloaded and processed, resulting in maps for each bicycle trip recorded. Participants then viewed each trip on a website and answered questions about the trip, including accuracy and route choice preferences. The former was used to correct the GPS data and account for under counting of bicycle travel.

GPS traces were matched to network links using ArcGIS and custom scripts written in the Python programming language. The network developed for this research included about 88,000 undirected links and 66,000 nodes. This network was constructed as much as possible to include all links available for bicycle travel. This included a large number of links not usually found in an auto travel modeling network such as minor residential streets, off-street bike and multiuse paths, alleyways, and some private roads explicitly open to bicycles. The bike network did not include facilities where bicycle use was legally restricted, mainly urban freeways. The base network was provided by Oregon Metro, the regional planning organization. Numerous improvements were made to allow us to link the GPS trip data to the network and to allow for route choice modeling. Particular attention was paid to coding overpasses, underpasses, and one-way streets correctly. In some cases, links had to be added to the network where "cut-throughs" and other informal or unmapped links were used by the participants. Spurious u-turns caused by GPS signal "bounce" were eliminated. After several screening steps, 1449 trips were available for this analysis. The data set did not include trips made exclusively for exercise purposes (e.g. a 15-mile loop ride) or trips that included transit. A full report describing the GPS data collection methods and the processes used to prepare the data is available (Dill and Gliebe, 2008).

For the route choice models, several network characteristics ("attributes") were added to the data. The City of Portland provided interpolated average daily traffic volumes for nearly all streets in the study area based on automated count data. The available volume estimates were used to estimate missing link volumes based on functional class. Turns were calculated using a combination of street name and geometry. A 10 m digital elevation model (DEM) was used to measure elevation gain and loss at roughly 10 m increments along each link. Bicycle facilities, grade separation, intersection control, and one-way restrictions were provided by Oregon Metro. When generating route alternatives, one-way streets were treated as open to bicycling but with additional impedance based on an observed speed reduction of 41%.

After screening out cyclists with only exercise trips, our dataset included observations for 154 participants over multiple trips. During the study, participants recorded an average of 2.5 non-exercise bicycle trips per day. About 30% of trips were commute trips (home to work or work to home). The average trip distance was 2.2 miles (3.5 km) for non-commute trips (e.g. shopping, errands, etc.) and 3.7 miles (6 km) for commute trips. Average speed (including stops) was 10 miles/h (16.1 km/h) for non-commute trips and 11.8 miles/h (19 km/h) for commute trips. In comparison, the sample of Zurich, Switerland trips in Menghini et al. (2010) averaged 0.62 miles (1 km) at 6.3 miles/h (10.1 km/h).

A little more than half (53%) of recorded miles were ridden on facilities with bicycle infrastructure, including bike lanes (29%), off-street paths (13%), and bike boulevards (11%). Bike boulevards are residential streets with traffic calming features to reduce auto speeds and volumes (e.g. speed humps, one-way restrictions on autos, chicanes, etc.), while giving bicycles increased priority at intersections, e.g. by eliminating stop signs in the boulevard direction and "flipping" them to the cross-direction traffic and adding crossing aids, including signals, at busy intersections. Observed paths were on average somewhat longer than the shortest network paths: by 12% for non-commute trips and 11% for commute trips. Further descriptive analysis is available in a separate report (Dill and Gliebe, 2008).

2.3. Choice set generation and model specification

Generating the set of alternative routes considered raised several challenges. The size and density of the Portland bicycle travel network greatly increased the task's complexity. In addition, the lack of existing revealed preference bicycle route choice studies demanded a careful rethinking of existing generation techniques. Common algorithms based on travel time and street hierarchy were not directly applicable, since bicycle travel times are not affected by speed limits, congestion, and functional class in the same ways as auto travel times.

We experimented with three common choice set generation methods: K-shortest paths, simulated shortest paths, and route labeling, none of which proved entirely satisfactory. The first two methods were developed for use with sparse auto networks. When applied to our bike network, they produced behaviorally unrealistic paths (e.g. paths that left and returned to the same corridor many times). We attempted to modify the methods using turn penalties, but the results remained poor both in terms of reasonableness and the reproduction of observed routes. Route labeling, in which a series of route attributes are minimized or maximized, produced behaviorally reasonable routes but produced only one or two alternatives for an unacceptably large number of routes. Initial model estimates with the route labeling choice sets suggested high sensitivity to the distance weighting factors specified.

Based on these experiments and our own hypotheses about bicyclists' choice set generation process, we developed a modified method of route labeling that would improve both attribute variation and reasonableness of routes for our unusually dense network (Broach et al., 2010). Route alternatives were chosen by maximizing individual criteria (e.g. percentage of route on designated bicycle facilities), subject to multiple distance constraint values within a defined range instead of a single arbitrary value as traditionally used in route labeling. The resulting shortest path deviations were calibrated to the entire sample of observed deviations to ensure that alternatives were reasonable and consistent with observed cyclist behavior. The new method reproduced a larger portion of observed routes than existing methods and did so more efficiently than the K-shortest path and simulation techniques. Readers are directed to the cited article for a full description of the calibrated labeling method and its behavioral rationale.

Applied to our bicycle travel network, the choice set generation algorithm produced a median of 20 alternative paths for each trip. The number of alternatives varied across choice situations, increasing with both trip distance and network density. For a small number of trips (15 out of 1464), no alternative to the chosen route was found. These "captive" trips were not included in the model estimation, since by our criteria the cyclist had no reasonable alternative route to choose.

Where alternate paths share common links, they also presumably have correlated error components. This violates the multinomial logit (MNL) model assumption of independently distributed errors across alternatives. From a statistical point of view, a MNL route choice model will tend to assign counter-intuitively high probabilities to routes that share common network links. From a behavioral point of view, we might say that the MNL considers overlapping routes distinct alternatives; whereas, cyclists may consider such routes jointly as minor variants of a single alternative. There are two options to overcome the overlapping routes problem (Frejinger and Blerlaire, 2007). A correction factor can be applied to partially adjust the utilities for overlap, leading to the Path-Size Logit (PSL) model. Alternatively, more complex model forms may be specified that allow for correlated errors, including the multinomial probit model, mixed logit models, and closed-form members of the generalized extreme value (GEV) class of models.

Due to the very large number of potential alternatives, we chose the PSL approach, retaining the underlying MNL structure. We recognized the need to be able to apply the model for prediction across a very complex, detailed network. This requirement made the specifications of overlapping route calculations and nest memberships needed for the various probit, mixed logit, and GEV models seem somewhat intractable over such a large computational space. In addition, it has been shown that more complex model forms may be particularly inconsistent when only a small proportion of potential alternatives can be sampled (Nerella and Bhat, 2004).

A path size factor was calculated directly from route alternatives and network geometry, avoiding direct calculation of correlations across alternatives. The general form for the j alternatives in choice set C_n is specified as:

$$PS_{in} = \sum_{a \in \Gamma_i} \frac{l_a}{L_i} \frac{1}{\sum_{j \in C_n} \left(\frac{L_i}{L_j}\right)^{\gamma} \delta_{aj}} \tag{1}$$

where Γ_i are the links in alternative i, l_a is the length of link a, L_i is the length of alternative i, and δ_{aj} equals 1 if j includes link a (Frejinger and Blerlaire, 2007). The parameter γ is a positive scaling term meant to penalize very long routes in a choice set. Fixing or estimating $\gamma > 0$ has been shown empirically to improve route choice model fit (Bekhor et al., 2006; Hoogendoorn-Lanser et al., 2005; Prato and Bekhor, 2006, 2007); however, it has recently been shown that $\gamma > 0$ can result in questionable utility corrections and illogical path probabilities (Frejinger and Blerlaire, 2007). In addition, our choice set generation method makes it unlikely that improbably long alternative paths will be included in our analysis. For these reasons, the path-size correction factor in Eq. (1) is used with $\gamma = 0$, essentially dropping the long-path correction factor and yielding the basic Path Size Logit (PSL) model (Ben-Akiva and Bierlaire, 1999).

While relatively simple, the PSL model has been shown to perform well relative to more complex model forms such as the cross-nested logit (CNL), although existing comparisons were performed with the generalized PS factor including $\gamma > 0$ (Bekhor et al., 2006; Prato and Bekhor, 2006, 2007). While nested logit models should outperform the PSL specification, they are limited in real network applications due to the huge number of parameters that would have to be estimated to exploit their full flexibility (Bekhor et al., 2006; Frejinger and Blerlaire, 2007).

This paper presents results obtained from the following specification of the Path Size Logit probability for alternative route i for observation n given choice set C_n is specified as:

$$\Pr(i|C_n) = \frac{\exp^{V_{in}+\ln(PS_{in})}}{\sum_{j\in C_n}\exp^{V_{jn}+\ln(PS_{jn})}} \tag{2}$$

where PS is the path size factor from Eq. (1) with $\gamma = 0$. Since PS will always fall between 0 and 1, $\ln(PS)$ will be negative, consistent with a utility reduction proportional to the degree of overlap. The utility function is linear-in-parameters.

It is likely that an individual's series of route choices are correlated to some extent. The inclusion of multiple trip purposes and the generally short period of observation probably limit such correlation. Furthermore, an investigation of commute trip sequences, which we might expect to be the most regular, showed noticeable route choice variation across trips. It did not seem as though these cyclists were "locked in" to a fixed route.

Controlling for potential panel effects in discrete choice models with unlabeled alternatives (i.e. alternatives that vary across observations) requires complex model forms with properties that are not entirely understood (Hsiao, 1986; Train, 2009). We tested mixed logit specifications that included individual-specific effects. Results suggested that mean parameter values were not particularly sensitive to panel effects, although there was evidence of some unobserved heterogeneity in the data. The mixed logit estimations exhibited instability, and there are general concerns about effects of distributional assumptions and estimator consistency when sampling alternatives from a large choice space (Hensher and Greene, 2003; Nerella and Bhat, 2004). For these reasons, further examination of panel effects and unobserved heterogeneity was left for future research, and trips were assumed to be independent for this analysis.

3. Results and discussion

Table 1 describes the variables used in the route choice model, including mean values and the proportion of alternative paths (out of a total of 29,090 paths) for which the variable is present. Table 2 presents the full estimation results from our final model specification. Estimation was performed using the freely available BIOGEME software (Bierlaire, 2003).

Since distance enters the model in log form, each of the other variables in the model have marginal rates of substitution that are constant with respect to the natural log of distance. The disutility of additional distance diminishes as distance increases but remains constant with respect to the percent change in distance. Table 3 presents the estimation results in terms of this distance trade-off, which may be thought of as the distance value of a unit change in each variable. The equivalent percent change in distance is non-linear with respect to the change in a given attribute, and can be calculated for non-unit changes using following equation:

$$\text{Equivalent }\%\Delta\text{ distance} = \left(\text{Exp}\left(\Delta\text{attribute} * \frac{\beta\_\text{attributes}}{\beta\_\ln(\text{dst})}\right) - 1\right) * 100 \tag{3}$$

where β is the estimated coefficient. In addition, Table 3 presents results for two separate models – commute trips and non-commute trips – which reveal some differences in route choice preference depending upon trip purpose.

3.1. Effects of route and facility characteristics

As expected, cyclists prefer shorter routes, holding other attributes equal. Log distance outperformed other distance specifications, suggesting that *relative* rather than *absolute* route deviations are what matter to cyclists. This result has some behavioral appeal. Implied is that a cyclist would be equally likely to go 1 mile out of her way on a 5 mile trip as 0.2 miles out of her way on a 1 mile trip. In other words, a fixed distance, say 1 mile, is perceived as more costly the shorter the trip. All else equal, a 1% increase in distance reduces the probability of choosing a route by about 5% and 9% for non-commute and commute trips, respectively. That cyclists are highly sensitive to distance is consistent with the observed data. Half of all observed trips were less than 10% longer than the shortest path, and 95% of trips were less than 50% longer.

Travel times in our sample were highly correlated with distance ($r = 0.93$) such that the two were more or less interchangeable. That said, there are probably some minor travel time effects embedded in some of the non-distance variables, particularly turns, intersections, and slope. The coefficients for these non-distance variables should be interpreted as the combination of travel time and non-travel time (e.g. perceived safety, effort, pleasantness, etc.) effects.

Turns likely delay cyclists, and they also add the mental cost of having to remember the correct sequence of turns. As expected, turn frequency is a significant negative factor in route choice. Once difficult left turns (across moderate to heavy traffic without a traffic signal) were accounted for, left and right turns were not significantly different, which seems reasonable. The model predicts that an additional turn per mile (0.6 turns/km) is equal to a 7.4% increase in non-commute distance and a 4.2% increase in commute distance.

Intersection crossings often delay cyclists, though the presence of a traffic control device (signal or stop sign) has an important bearing on the amount of delay. Depending on the amount of conflicting traffic, signals might be attractive features for cyclists trying to travel through or make turns across busy intersections. Significant negative coefficients confirm

Table 1
Variable descriptions.

Variable	Description	Mean	Proportion of alternative paths for which attribute is present (n_p = 29,090) (%)
Bridge w/bike lane	Bridge with on-street bike lane	Dummy variable	5
Bridge w/sep. facility	Bridge with improved, separated bike facility	Dummy variable	22
Prop. upslope 2–4%	Proportion of route along links with average upslope (gain/length) of 2–4%	0.10	90
Prop. upslope 4–6%	Proportion of route along links with average upslope (gain/length) of 4–6%	0.03	70
Prop. upslope 6%+	Proportion of route along links with average upslope (gain/length) of 6%+	0.02	68
Distance (mile)	Distance of route in miles	4.48	100
Path size (0–1, 1 = unique)	Path size (formula provided in text)	0.31	100
Left turn, unsig., AADT 10–20k (mile)	Left turn without traffic signal and parallel traffic volume 10,000–20,000 per day	0.11	36
Left turn, unsig., AADT 20k+(/km)	Left turn without traffic signal and parallel traffic volume 20,000+ per day	0.08	18
Prop. bike boulevard	Proportion of route on designated bicycle boulevard (improved neighborhood street with traffic calming, diversion, signage, and enhanced right of way)	0.10	53
Prop. bike path	Proportion of route on off-street, regional bike path (i.e. not minor park paths, sidewalks, etc.)	0.04	41
Prop. AADT 10–20k w/o bike lane	Proportion of route on streets with traffic volume 10,000–20,000 per day without a bike lane	0.08	73
Prop. AADT 20–30k w/o bike lane	Proportion of route on streets with traffic volume 20,000–30,000 per day without a bike lane	0.04	46
Prop. AADT 30k+ w/o bike lane	Proportion of route on streets with traffic volume 30,000+ per day without a bike lane	0.02	26
Traffic signal exc. right turns (mile)	Left turns and straight movements through traffic signals per mile	1.84	90
Stop signs (mile)	Turns or straight movements through stop signs per mile	3.12	95
Turns (mile)	Left and right turns per mile	3.64	100
Unsig. cross AADT 10k+ right turns (mile)	Right turns at unsignalized intersections with cross traffic volume 10,000+ per day	0.16	44
Unsig. cross AADT 5–10k exc. right turns (mile)	Left turns and through movements at unsignalized intersections with cross traffic volume 5000–10,000 per day	0.56	72
Unsig. cross AADT 10–20k exc. right turns (mile)	Left turns and through movements at unsignalized intersections with cross traffic volume 10,000–20,000 per day	0.42	72
Unsig. cross AADT 20k+ exc. right turns (mile)	Left turns and through movements at unsignalized intersections with cross traffic volume 20,000+ per day	0.16	52

Table 2
Route choice model estimation results.

Variable	Est. coeff.	*t*-Stat
Ln(distance)	−5.22	−10.9**
Ln(distance) ∗ commute	−3.76	−5.14**
Turns (mile)	−0.371	−15.4**
Prop. upslope 2–4%	−2.85	−4.57**
Prop. upslope 4–6%	−7.11	−6.11**
Prop. upslope ⩾6%	−13.0	−8.57**
Traffic signal exc. right turns (mile)	−0.186	−5.73**
Stop sign. (mile)	−0.0483	−2.10*
Left turn, unsig., AADT 10–20k (mile)	−0.782	−4.19**
Left turn, unsig., AADT 20k+ (mile)	−1.87	−4.70**
Unsig. cross AADT ⩾10k right turn (mile)	−0.338	−2.32**
Unsig. cross AADT 5–10k exc. right turn (mile)	−0.363	−5.39**
Unsig. cross AADT 10–20k exc. right turn (mile)	−0.516	−5.39**
Unsig. cross AADT 20k+ exc. right turn (mile)	−2.51	−11.5**
Prop. bike boulevard	1.03	5.17**
Prop. bike path	1.57	4.64**
Prop. AADT 10–20k w/o bike lane	−1.05	−3.02**
Prop. AADT 10–20k w/o bike lane ∗ commute	−1.77	−2.28*
Prop. AADT 20–30k w/o bike lane	−4.51	−6.04**
Prop. AADT 20–30k w/o bike lane ∗ commute	−3.37	−2.24*
Prop. AADT 30k+ w/o bike lane	−10.3	−4.67**
Prop. AADT 30k+ w/o bike lane ∗ commute	−8.59	−1.96*
Bridge w/bike lane	1.81	−4.71**
Bridge w/sep. bike facility	3.11	−4.96**
Ln(path size)	1.81	20.78**
Number of observations	1449	
Null log-likelihood	−4058.7	
Final log-likelihood	−3020.0	
Rho-square	0.256	

* Significant at the 5% level.
** Significant at the 1% level.

Table 3
Relative attribute values (unit change).

Attribute	Distance value (% dist.)	
	Non-commute	Commute
Turns (mile)	7.4	4.2
Prop. upslope 2–4%	72.3	37.1
Prop. upslope 4–6%	290.4	120.3
Prop. upslope ⩾6%	1106.6	323.9
Traffic signal exc. right turns (mile)	3.6	2.1
Stop sign. (mile)	0.9	0.5
Left turn, unsig., AADT 10–20k (mile)	16.2	9.1
Left turn, unsig., AADT 20k+(mile)	43.1	23.1
Unsig. cross AADT ⩾10k right turn (mile)	6.7	3.8
Unsig. cross AADT 5–10k exc. right turn (mile)	7.2	4.1
Unsig. cross AADT 10–20k exc. right turn (mile)	10.4	5.9
Unsig. cross AADT 20k+ exc. right turn (mile)	61.7	32.2
Prop. bike boulevard	−17.9	−10.8
Prop. bike path	−26.0	−16.0
Prop. AADT 10–20k w/o bike lane	22.3	36.8
Prop. AADT 20–30k w/o bike lane	137.3	140.0
Prop. AADT 30k+ w/o bike lane	619.4	715.7
Bridge w/bike lane	−29.3	−18.2
Bridge w/sep. bike facility	−44.9	−29.2

that, in general, traffic signals and, to a lesser extent, stop signs decrease the utility of a route. However, where conflicting traffic volumes are high, the larger negative coefficients on unsignalized intersection movements imply that the positive effects of signals outweigh the negative in such locations. Whether this is because signals actually reduce delay at busy intersections, because they increase perceived safety, or some combination of the two is unclear. Right turns were excluded from most of the variables because such movements avoid most of the traffic conflicts and delays. Model fit with different specifications supported this distinction. On a 1 mile non-commute trip, a cyclist would be willing to travel about 10.4% out of her way to avoid an unsignalized crossing where cross traffic averaged 10,000–20,000 vehicles per day (5.9% for a commute trip). To avoid a left turn at an unsignalized intersection with through traffic volume of 10,000–20,000 vehicles per day, a cyclist would be willing to travel about 16.2% (9.1% commute) farther on a 1 mile trip. To our knowledge, this is the first such result demonstrating the importance to cyclists of signalized intersections at busy street crossings.

Many permutations of elevation change and slope were tested, including cumulative gain and loss, average and maximum slope, and several non-linear slope variables. The best performing specification was proportion of route length within three categories of average positive slope (gain/distance): 2–4%, 4–6%, and 6%. For example, a link traversing 500 ft (150 m) with 10 ft (3 m) gross gain along the traversal would have an average upslope of 2% and would be coded as 500 ft (150 m) in the 2–4% upslope category. Our model indicates that a cyclist would be willing to pedal 1.72 flat miles (1.37 miles commuting) if the alternative were 1 mile of 2–4% upslope.

Four bike-specific facility types were included in the final model: bike boulevards, off-street bike baths, bike lanes, and separated bike facilities on bridges. In addition, bike lanes were further divided into categories based on traffic volumes, and a separate category for bridge bike lanes was included. In Portland, bike boulevards are always on low traffic, neighborhood streets. Bike paths by definition have no motorized traffic. Designated bike routes were also tested as a facility type. As expected, these unimproved bike routes (streets with signage, but no other improvements) were insignificant factors once the other variables were included in the model.

The models showed a preference for separated bike paths, followed by bike boulevards, even after controlling for all of the other variables in the model. For non-commute trips, travel on bike boulevards is equivalent to decreasing distance by almost 17.9% (10.8% for commute trips). Travel on bike paths is equivalent to reducing distance by 26.0% for non-commute trips and 16.0% for commute trips. The boulevard and path parameters were significantly different at the 10% level ($p \leqslant 0.09$). We tried many permutations of bike lane variables. Because bike lanes in Portland are almost exclusively on busy arterial streets, it was difficult to tease out the effect of bike lanes from that of traffic volume. In the final specification, bike lanes more or less exactly offset the negative effects of adjacent traffic but had no residual value of their own. This is consistent with the idea that bike lanes provide cyclists their own space separate from traffic but beyond this are no more or less attractive than a basic low traffic volume street.

All else equal, the estimation suggests cyclists are willing to go considerably out of their way to use a bike boulevard or bike path rather than an arterial bike lane. This is not to suggest bike lanes are not valuable; if the alternative is an arterial street without a bike lane, then a designated lane has considerable value to cyclists. These results may not transfer to places where bike lanes are placed on low traffic volume streets.

On streets without bike lanes, cyclists are highly sensitive to high traffic volumes. In fact, the estimation suggests that for non-commute trips, streets with traffic volumes in excess of 20,000 vehicles per day would be used only if lower traffic alternatives required very long detours (in excess of 100%) or other strong deterrents such as steep hills. Within the city, Portland's bike network is fairly dense and well-developed, and it is not clear that this result would hold in places with a sparser network of bike facilities. It seems unlikely that a cyclist would actually choose a route seven times longer to avoid traveling on a highway without a bike lane; more likely, he would not travel by bicycle at all. Nonetheless, the result underscores the sensitivity of cyclists to high volumes of mixed traffic.

The Willamette River splits separates Portland's central business district from largely residential areas east of the river. A little more than a quarter of observed trips crossed the Willamette on one of eight bridges available to bikes. Sampled cyclists were quite sensitive to bridge bike facilities. For non-commute trips, a bridge with a bike lane was equivalent to a 29% reduction in distance up to almost 45% for a separated bridge facility. Clearly, bridge facilities have a strong influence on cyclists' route choices for trips crossing the river. It should be noted, however, that very few cycling trips were observed on bridges without any bike facility (sidewalks designed for pedestrian use were not considered bike facilities), which may make the estimation less precise.

3.2. Non-commute vs. commute trips

In general, the model suggests that commuting cyclists are relatively more sensitive to distance and less sensitive to most other variables compared to cyclists riding for other utilitarian purposes. Commuting cyclists are likely under greater time pressure to reach their destination in the work direction. It is also possible that the more habitual nature of commute trips makes commuters more aware of distance and time differences among competing routes. It is also possible that commuters' knowledge of the route allows them to mitigate some of the delay and safety issues on commute trips. For example, they may learn the timing of traffic lights, how best to navigate intersections, and where to make difficult turns.

Exceptions to the above are found in the facility traffic volume attributes. Cyclists on commute trips are somewhat more sensitive to riding in high volumes of mixed traffic than on non-commute trips. The finding is consistent with the fact commutes are more likely to occur during periods of peak traffic. Since our traffic volume variable reflects average volumes, it likely overstates the amount of traffic for off-peak trips.

3.3. Path-size parameter

The path-size parameter estimate's positive coefficient is consistent with theory (Table 2). It is significantly different from 1.0, which would be the expected value if the path-size parameter captured only the statistical error introduced by the independence from irrelevant alternatives (IIA) property of the MNL model. It has been suggested that the path-size parameter should not be arbitrarily fixed to 1.0, since it may have a meaningful behavioral interpretation (Frejinger and Blerlaire, 2007). In our case, estimating the parameter significantly improved model fit. Fixing the path-size parameter to 1.0 has the effect of reducing the magnitude of the distance coefficient while leaving the other parameters more or less unchanged. Since generated alternatives tend to cluster around the shortest-path, the greater than expected path-size correction may indicate unobserved disutility factors along shortest-path corridors.

4. Conclusions

This paper outlined the development of a unique bicycle route choice model based on revealed preference GPS data. A new choice set generation algorithm, dubbed the Calibrated Labeling Method, was developed to generate reasonable sets of alternatives after existing methods proved unsatisfactory. The final model specification resulted in a rich range of insights into cyclist preferences. Some of the factors included in the model, such as bicycle boulevards, have not been tested before with revealed preference route choice data.

With respect to facility type, the model revealed a preference first for separated paths, followed by bicycle boulevards. Striped bike lanes were only preferred when low-traffic neighborhood streets were not an option, though they were highly valued compared to high traffic streets (20,000 AADT or higher) without a striped lane. The preference for local streets and off-street paths, particularly over arterials, is consistent with findings from Winters et al. (2010) which compared a cyclist's typical route based upon recall to the shortest path. Sener et al. (2009) also found that avoiding high traffic was one of the two most important factors in route choice, along with minimizing time (for commuting).

The findings from our model suggest that even confident cyclists prefer routes that reduce exposure to motor vehicle traffic, since most of the study participants were regular bicyclists, averaging 2–3 bicycle trips per day. These findings contrast with some stated preference studies that found that experienced cyclists preferred lanes over paths or no facilities at all (Akar and Clifton, 2009; Antonakos, 1994; Bureau of Transportation Statistics, 2004; Hunt and Abraham, 2007; Sener et al., 2009; Stinson and Bhat, 2003; Taylor and Mahmassani, 1996; Tilahun et al., 2007). The difference in findings may be attributed to the methods, which, even when designed carefully, do not reflect the reality of an individual's route choice options. In this case, the network of separate paths in Portland may be more extensive and/or located to better facilitate utilitarian travel than in other locations. Cyclists in some US cities may have only experienced separate paths that are distant from trip destinations and those biases may influence their responses to stated preference surveys. In addition, some paths attract high volumes of pedestrians and other users that may slow down commuter cyclists; these experiences may also influence responses to stated preference questions. Sampling methods may also influence findings. For example, Sener et al. (2009) sampled from bicycle group e-mail lists where cyclists may have more of a "road warrior" (p. 530) mentality and included both commuters and recreational cyclists. Using revealed preference data, Larsen and El-Geneidy (2011) did find that regular utilitarian cyclists were less likely than recreational cyclists to use a bike lane or path. But, for non-recreation trips, the cyclists still went the furthest out of their way for an off-street path, compared to on-street facilities.

The value cyclists placed on bicycle boulevards is an important finding. This type of facility is a relatively new concept in the US and therefore has not been tested in any of the existing research. Our findings show that bike boulevards have high and inherent value to cyclists, even beyond the detailed facility variables we were able to measure. In other words, there is something more to a bike boulevard than low traffic volumes, improved street crossings, and "flipped" stop signs. The something more may be explained by attributes we were unable to measure, such as parking and traffic speeds, or perhaps something more subtle like perceived safety in numbers or simplified navigation. The results leave this intriguing question for future research and direct implications for policy and planning. Bicycle boulevards are an option for existing and new residential neighborhoods with well-connected street systems. In most cases, costs are lower than separated paths, as they do not require new right-of-way, grading, or other significant engineering.

Our findings regarding the relative value of different types of facilities are influenced, in part, by the characteristics of the network available to the study participants, making direct comparisons to other studies more difficult. For example, the Portland region's network included bicycle boulevards, while the Montreal network examined by Larsen and El-Geneidy (2011) did not, but did include on-street separated paths (e.g. cycletracks) which were not present in Portland at the time of the study. Meaningful comparisons to Menghini et al. (2010) are difficult because the cyclist samples, setting, choice set generation, and model forms are substantially different. Both models revealed preferences for direct routes, designated bike facilities, and avoidance of steep slopes. The network data available for this study allowed us to include several key variables not available in the Zurich study: specific bicycle facility types, traffic volumes, and detailed intersection and turn attributes. As GPS data collection becomes more common, it will be useful to compare results from different locations, using similar measures of the bicycle facility network and modeling techniques.

In addition, our findings are also based upon a sample largely made up of confident, regular cyclists. For cycling rates to increase significantly, a wider range of people need to cycle. Therefore, it is important to research the preferences of noncyclists, occasional cyclists, and cyclists who only ride for recreation (e.g. mountain biking or bicycling on vacation) but would consider cycling for transportation in different circumstances, including better infrastructure. We did test for differences between regular and occasional cyclists, but the sample size (20 occasional cyclists making 90 trips) did not allow us to draw conclusions. We also tested, but did not find significant differences by gender, age group, or parental status. The lack of differences by demographic group may be due to the sample size.

The results highlight the importance for transportation professionals of not only building bike lanes, paths, and boulevards, but building them using comprehensive designs that consider all aspects of the route. Details like busy street crossing treatments, route ‘‘jogs’’ necessitating extra turns, and route planning to avoid slopes may prove as or more important than the facility itself. One of the most important influential attributes found in our model were slopes above 2%; cyclists go significant distances to avoid such hills. Menghini et al. (2010), which used revealed preference GPS data, also found that cyclists avoided steep maximum gradients. However, this finding contrasts with those of Sener et al. (2009) and Stinson and Bhat (2003) which found a stated preference for moderate hills (compared to flat terrain), particularly for recreational cycling. These differences may be explained by the sample (discussed above), the fact that our model did not include trips made solely for recreation or exercise, and the use of descriptive terms rather than actual slope. Moreover, some cyclists may say that they want some hills as a challenge or to increase health benefits, but when it comes to actually riding, they choose differently.

Intersection characteristics can be just as important as bicycle-specific infrastructure. Our cyclists generally avoided stops signs and traffic signals, except when they needed to cross or turn left at high-traffic streets, in which case traffic signals were valued. This is consistent with Winters et al. (2010) which found that the presence of bicycle-actuated signals helped explain why cyclists’ detoured at least 10% beyond the shortest path. While our model did not specify bike actuation, it did confirm the importance of signals to aid crossing busy streets. Sener et al. (2009) also found that cyclists preferred routes with fewer stop signs and lights, but did not distinguish between lights that might facilitate difficult crossings. Changing the direction of stop signs along a bicycle route and providing signals to facilitate crossing high-traffic streets are two features of bicycle boulevards that may be applied to any bicycle route. However, without the addition of other traffic calming features, such routes may become attractive to motorists as well, possibly negating their value.

In addition to helping transportation professionals plan and design new infrastructure to improve cycling conditions, the findings can be used to improve travel demand models for predicting bicycle travel and to enhance route-finding tools available to cyclists. Portland Metro has incorporated the route choice model results developed here into the trip distribution, mode choice, and network assignment steps within their regional travel demand model. With these changes, travel forecasts are now sensitive to both planned bike infrastructure changes and the impact of predicted future traffic volumes on bike travel. There are an increasing number of on-line tools to assist people in finding a bicycle route for a particular trip. The improved understanding of cyclists’ preferences can make those tools more relevant and effective (Su et al., 2010). Our findings that route choices differ for commute vs. other utilitarian travel indicate that this could be an option to include in route-finding tools.

Acknowledgments

The Active Living Research program of the Robert Wood Johnson Foundation and the Oregon Transportation Research and Education Consortium (OTREC) provided funding for much of the original data collection, but were not involved in the analysis, interpretation, or manuscript preparation. The authors thank Oregon Metro for providing the base street network, the Portland Bureau of Transportation for providing traffic volume estimates, and Jack Newlevant for his tireless collection of bicycle network data. Oregon Metro and the Oregon Transportation Research and Education Consortium (OTREC) provided funding for the model development. Of course, special thanks is due to the 164 Portland cyclists who took time to gather the GPS data for the study.

References

Akar, G., Clifton, K.J., 2009. The influence of individual perceptions and bicycle infrastructure on the decision to bike. Transportation Research Record: Journal of the Transportation Research Board 2140, 165–172.

Antonakos, C., 1994. Environmental and travel preferences of cyclists. Transportation Research Record (1438), 25–33.

Aultman-Hall, L., Hall, F.L., Baetz, B.B., 1998. Analysis of bicycle commuter routes using geographic information systems: implications for bicycle planning. Transportation Research Record 1578, 102–110.

Bekhor, S., Ben-Akiva, M.E., Ramming, M.S., 2006. Evaluation of choice set generation algorithms for route choice models. Annals of Operations Research 144 (1), 235–247.

Ben-Akiva, M.E., Bierlaire, M., 1999. Discrete choice methods and their applications to short term travel decisions. In: Hall, R. (Ed.), Handbook of Transportation Science. Kluwer, Dordrecht, The Netherlands, pp. 5–34.

Bierlaire, M., 2003. BIOGEME: a free package for the estimation of discrete choice models. In: Paper presented at the Proceedings of the 3rd Swiss Transportation Research Conference.

Bohle, W., 2000. Attractiveness of bicycle-facilities for the users and evaluation of measures for the cycle-traffic. In: Paper presented at the Velo Mondial 2000. <http://www.velomondial.net/velomondiall2000/Html/PROCEED/AINDEX.HTM>.

Broach, J., Gliebe, J., Dill, J., 2010. Calibrated labeling method for generating bicyclist route choice sets incorporating unbiased attribute variation. Transportation Research Record (2197), 89–97.

Bureau of Transportation Statistics, 2004. How Bike Paths and Lanes Make a Difference (No. 11). Bureau of Transportation Statistics, Washington, DC.

Cervero, R., Duncan, M., 2003. Walking, bicycling, and urban landscapes: evidence from the San Francisco bay area. American Journal of Public Health 93 (9), 1478–1483.

de Geus, B., De Bourdeaudhuij, I., Jannes, C., Meeusen, R., 2008. Psychosocial and environmental factors associated with cycling for transport among a working population. Health Education Research 23 (4), 697–708.
Dill, J., 2009. Bicycling for transportation and health: the role of infrastructure. Journal of Public Health Policy 30 (S1), S95–S110.
Dill, J., Carr, T., 2003. Bicycle commuting and facilities in major U.S. cities: if you build them, commuters will use them. Transportation Research Record Journal of the Transportation Research Board 1828, 116–123.
Dill, J., Gliebe, J., 2008. Understanding and Measuring Bicycling Behavior: a Focus on Travel Time and Route Choice. Oregon Transportation Research and Education Consortium, Portland, OR.
Dill, J., Voros, K., 2007. Factors affecting bicycling demand: initial survey findings from the Portland, Oregon, Region. Transportation Research Record: Journal of the Transportation Research Board 2031, 9–17.
Emond, C.R., Tang, W., Handy, S.L., 2009. Explaining gender difference in bicycling behavior. In: Paper Presented at the 88th Annual Meeting of the Transportation Research Board.
Frejinger, E., Blerlaire, M., 2007. Capturing correlation with subnetworks in route choice models. Transportation Research Part B – Methodological 41 (3), 363–378.
Garrard, J., Rose, G., Lo, S.K., 2008. Promoting transportation cycling for women: the role of bicycle infrastructure. Preventive Medicine 46 (1), 55–59.
Hensher, D.A., Greene, W.H., 2003. The mixed logit model: the state of practice. Transportation 30 (2), 133–176.
Hoogendoorn-Lanser, S., van Nes, R., Bovy, P., 2005. Path size modeling in multimodal route choice analysis. Transportation Research Record: Journal of the Transportation Research Board 1921, 27–34.
Howard, C., Burns, E.K., 2001. Cycling to work in phoenix: route choice, travel behavior, and commuter characteristics. Transportation Research Record 1773, 39–46.
Hsiao, C., 1986. Analysis of Panel Data. Cambridge UP, Cambridge.
Hunt, J.D., Abraham, J.E., 2007. Influences on bicycle use. Transportation 34 (4), 453–470.
Jackson, M.E., Ruehr, E.O., 1998. Let the people be heard – San Diego County bicycle use and attitude survey. Transportation Research Record 1636 (1636), 8–12.
Jensen, S.U., 2007. Pedestrian and bicycle level of service on roadway segments. In: Paper presented at the 86th Annual Meeting of the Transportation Research Board.
Krizek, K.J., 2006. Two approaches to valuing dome of bicycle facilities' presumed benefits. Journal of the American Planning Association 72 (3), 309–320.
Krizek, K.J., El-Geneidy, A., Thompson, K., 2007. A detailed analysis of how an urban trail system affects cyclists' travel. Transportation 34 (5), 611–624.
Landis, B.W., Vattijuti, V.R., Brannick, M.T., 1998. Real-time human perceptions: toward a bicycle level of service. Transportation Research Record 1578, 119–126.
Larsen, J., El-Geneidy, A., 2011. A travel behavior analysis of urban cycling facilities in Montreal Canada. Transportation Research Part D 16 (2), 172–177.
Menghini, G., Carrasco, N., Schussler, N., Axhausen, K.W., 2010. Route choice of cyclists in Zurich. Transportation Research Part A – Policy and Practice 44 (9), 754–765.
Nelson, A.C., Allen, D., 1997. If you build them, commuters will use them. Transportation Research Record 1578, 79–83.
Nerella, S., Bhat, C., 2004. Numerical analysis of effect of sampling of alternatives in discrete choice models. Transportation Research Record: Journal of the Transportation Research Board 1894 (-1), 11–19.
Parkin, J., Wardman, M., Page, M., 2007. Models of perceived cycling risk and route acceptability. Accident Analysis and Prevention 39 (2), 364–371.
Prato, C., Bekhor, S., 2006. Applying branch-and-bound technique to route choice set generation. Transportation Research Record: Journal of the Transportation Research Board 1985 (-1), 19–28.
Prato, C., Bekhor, S., 2007. Modeling route choice behavior: how relevant is the composition of choice set? Transportation Research Record: Journal of the Transportation Research Board 2003 (-1), 64–73.
Pucher, J., Buehler, R., 2005. Cycling trends and policies in Canadian cities. World Transport Policy and Practice 11 (1), 43–61.
Pucher, J., Dill, J., Handy, S., 2010. Infrastructure, programs, and policies to increase bicycling: an international review. Preventive Medicine 50 (Suppl. 1), S106–125.
Rose, G., Marfurt, H., 2007. Travel behaviour change impacts of a major ride to work day event. Transportation Research Part A: Policy and Practice 41 (4), 351–364.
Sener, I.N., Eluru, N., Bhat, C.R., 2009. An analysis of bicycle route choice preferences in Texas, U.S. Transportation 36, 511–539.
Shafizadeh, K., Niemeier, D., 1997. Bicycle journey-to-work: travel behavior characteristics and spatial analysis. Transportation Research Record 1578, 84–90.
Stinson, M., Bhat, C., 2003. Commuter bicyclist route choice: analysis using a stated preference survey. Transportation Research Record 1828, 107–115.
Su, J.G., Winters, M., Nunes, M., Brauer, M., 2010. Designing a route planner to facilitate and promote cycling in Metro Vancouver, Canada. Transportation Research Part A – Policy and Practice 44 (7), 495–505.
Taylor, D., Mahmassani, H., 1996. Analysis of state preferences for intermodal bicycle-transit interfaces. Transportation Research Record 1556, 86–95.
Tilahun, N.Y., Levinson, D.M., Krizek, K.J., 2007. Trails, lanes, or traffic: valuing bicycle facilities with an adaptive stated preference survey. Transportation Research Part A – Policy and Practice 41 (4), 287–301.
Train, K., 2009. Discrete Choice Models with Simulation, second ed. Cambridge University Press, Cambridge, <http://elsa.berkeley.edu/books/choice2.html>.
Vernez-Moudon, A.V., Lee, C., Cheadle, A.D., Collier, C.W., Johnson, D., Schmid, T.L., et al, 2005. Cycling and the built environment, a US perspective. Transportation Research Part D – Transport and Environment 10 (3), 245–261.
Winters, M., Teschke, K., 2010. Route preferences among adults in the near market for bicycling: findings of the cycling in cities study. American Journal of Health Promotion 25 (1), 40–47.
Winters, M., Teschke, K., Grant, M., Setton, E.M., Brauer, M., 2010. How far out of the way will we travel? Built environment influences on route selection for bicycle and car travel. Transportation Research Record (2190), 1–10.
Yang, L., Sahlqvist, S., McMinn, A., Griffin, S.J., Ogilvie, D., 2010. Interventions to promote cycling: systematic review. British Medical Journal 341, 10.