



# Short-term planning and policy interventions to promote cycling in urban centers: Findings from a commute mode choice analysis in Barcelona, Spain

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## ABSTRACT

**Background:** Cycling for transportation has become an increasingly important component of strategies to address public health, climate change, and air quality concerns in urban centers. Within this context, planners and policy makers would benefit from an improved understanding of available interventions and their relative effectiveness for cycling promotion. We examined predictors of bicycle commuting that are relevant to planning and policy intervention, particularly those amenable to short- and medium-term action.

**Methods:** We estimated a travel mode choice model using data from a survey of 765 commuters who live and work within the municipality of Barcelona. We considered how the decision to commute by bicycle was associated with cycling infrastructure, bike share availability, travel demand incentives, and other environmental attributes (e.g., public transport availability). Self-reported and objective (GIS-based) measures were compared. Point elasticities and marginal effects were calculated to assess the relative explanatory power of the independent variables considered.

**Results:** While both self-reported and objective measures of access to cycling infrastructure were associated with bicycle commuting, self-reported measures had stronger associations. Bicycle commuting had positive associations with access to bike share stations but inverse associations with access to public transport stops. Point elasticities suggested that bicycle commuting has a mild negative correlation with public transport availability (−0.136), bike share availability is more important at the work location (0.077) than at home (0.034), and bicycle lane presence has a relatively small association with bicycle commuting (0.039). Marginal effects suggested that provision of an employer-based incentive not to commute by private vehicle would be associated with an 11.3% decrease in the probability of commuting by bicycle, likely reflecting the typical emphasis of such incentives on public transport.

**Conclusions:** The results provide evidence of modal competition between cycling and

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public transport, through the presence of public transport stops and the provision of public transport-oriented travel demand incentives. Education and awareness campaigns that influence perceptions of cycling infrastructure availability, travel demand incentives that encourage cycling, and policies that integrate public transport and cycling may be promising and cost-effective strategies to promote cycling in the short to medium term.

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## 1. Introduction

The negative consequences of automobile dependency have become widely recognized in recent decades, prompting cities across the globe to invest in transportation alternatives with the potential to improve public health, reduce air pollution and carbon emissions, and relieve traffic congestion (Pucher et al., 2010b; de Nazelle et al., 2011; Deakin, 2001). As an active travel mode with physical activity benefits and no direct emissions, cycling has played an increasingly prominent role in these efforts to reduce automobile use and create more sustainable transportation networks in urban centers (Handy et al., 2014).

Cycling is often framed as a public health strategy, given growing evidence of its importance for physical activity and thus its potential to reduce associated chronic diseases. Ecological studies have found that countries with higher levels of active transportation (walking and cycling) have higher percentages of adults meeting minimum weekly physical activity recommendations and lower prevalence of obesity and diabetes (Pucher et al., 2010a; Bassett et al., 2008). These findings have been echoed in individual-level studies and systematic reviews, which have shown that active transportation is positively associated with physical activity and inversely associated with the risks of obesity, cardiovascular disease, and all-cause mortality (Wanner et al., 2012; Hamer and Chida, 2008; Andersen et al., 2000; Matthews et al., 2007). Importantly, recent work has suggested that bicycle commuting adds to overall physical activity, rather than replacing other forms of physical activity (Donaire-Gonzalez et al., 2015). Cycling in proximity to vehicles also entails certain health risks, including injuries and fatalities from crashes and increased exposure to air pollutants (Pucher and Dijkstra, 2003; Peden et al., 2004; Briggs et al., 2008; de Nazelle and Rodriguez, 2009). Although emerging research suggests that the benefits of increased physical activity may outweigh these risks (Mueller et al., 2015; Schepers et al., 2015; Rojas-Rueda et al., 2011; Hartog et al., 2010), these concerns persist and indicate a need for well-designed infrastructure that promotes safety, limits air pollution exposure, and thus maximizes the potential health benefits of cycling.

At the same time, cycling has become an important travel mode in strategies to promote low-carbon cities. Such strategies have been enacted in developed and developing countries, to varying degrees, in order to address the climate change challenges that result from fossil fuel consumption in the transportation sector. As a leading example, Copenhagen has incorporated cycling into its goal of becoming carbon neutral by 2025, with specific objectives including a 50% commute mode share for cycling and a 75% combined mode share of walking, cycling, and public transport for all trip purposes (City of Copenhagen, 2012). Rio de Janeiro has incorporated cycling into its Low-Carbon City Development Program (LCCDP), which includes plans to double the city's bicycle network and implement a bicycle sharing program in pursuit of reduced carbon emissions (The World Bank, 2013a). To encourage this type of growth in developing cities worldwide, the World Bank has published LCCDP plan preparation guidelines that include cycling recommendations (The World Bank, 2013b). As the World Bank's Low-Carbon Livable Cities (LC<sup>2</sup>) initiative is enacted to support low-carbon strategies in 300 of the world's largest developing cities (The World Bank, 2013c), and as the mayors of 491 cities join together in a commitment to reduce greenhouse gas emissions as part of the recent Compact of Mayors (Compact of Mayors, 2015), the role of cycling in international climate change mitigation efforts is likely to become even more prominent.

The importance of cycling for public health and low-carbon mobility—coupled with the potential for non-motorized transportation to reduce congestion and generate corresponding gains in air quality (de Nazelle et al., 2011; Woodcock et al., 2009)—has prompted many cities to implement policies and invest in infrastructure to promote cycling. While bicycle lanes and separated paths are common interventions, cities have increasingly turned to policy and programmatic approaches such as bicycle sharing and travel demand management programs (Pucher et al., 2010b). The strategies available to planners and policy makers for encouraging cycling are diverse, with varying impacts, time horizons, and potential synergies. Within this context, decision makers would benefit from an enhanced understanding of the relative influence of various strategies on cycling and how they might be combined and prioritized in practice.

In this study, we examined how planning and policy interventions are associated with bicycle commuting in Barcelona, Spain. Compared to many Northern European cities, Barcelona has a relatively small cycling mode share equating to just 1.3% of trips in the metropolitan area (Autoritat del Transport Metropolità, 2013). To reverse this trend, the city has pursued numerous policies over the past decade to be friendlier toward cyclists. Key changes include the addition of nearly 60 km of bicycle lanes between 2007 and 2012 (an increase of 44%), expansion of bicycle parking throughout the city, and the 2007 implementation of *Bicing*, a bicycle sharing program serving nearly 100,000 annual subscribers as of February 2016 (Bicing, 2016).

To evaluate these efforts and other potential cycling strategies, we estimated a travel mode choice model that explored factors associated with bicycle commuting among adults who both live and work in the municipality of Barcelona. The data

were drawn from a travel survey conducted in 2011–2012, after the aforementioned cycling interventions had taken place. We modeled the dichotomous choice between cycling and non-cycling modes and examined how this choice was associated with planning and policy factors that are amenable to short- to medium-term intervention, including cycling infrastructure, *Bicing* availability, and travel demand incentives. These short- to medium-term interventions are actionable and may produce early wins that can have important population health impacts. We also considered access to public transport stops in order to assess modal competition, and land use characteristics in order to explore longer-term planning strategies that may support a modal shift toward cycling.

Our research aimed to answer the following questions: (1) How are these planning and policy factors associated with the decision to commute by bicycle, and what are the relative magnitudes of these associations? (2) Do objective and self-reported measures of cycling infrastructure and *Bicing* availability have distinct associations with bicycle commuting? The first question addresses how planning and policy interventions are related to cycling and provides an indication of which strategies could have the strongest influence on cycling mode share. This type of information is useful for planners and policy makers deciding how to spend scarce resources and has been identified as an important research direction for cycling promotion (Handy et al., 2014). The second question is critical for interventions because objective and self-reported environmental measures often have varying associations with travel behavior and may point to different types of strategies (e.g., infrastructure, education and awareness campaigns). Through these explorations, we provide a nuanced understanding of how planning and policy interventions can be prioritized and coordinated in order to promote cycling in urban centers.

## 2. Literature review

Research on cycling mode choice has grown considerably during the past two decades, coinciding with an increasing emphasis on cycling as a sustainable urban transportation strategy. Broadly, this work has found that decisions about cycling are influenced by a variety of characteristics at the level of the trip (e.g., distance, travel time, cost), the individual (e.g., sociodemographics, attitudes and norms, life events), and the environment (e.g., infrastructure, built environment, topography) (Handy et al., 2014; Heinen et al., 2010). In line with the aims of the present study, our review focuses on the latter category with an emphasis on the planning and policy environment. We organize this discussion around the major variable types addressed in our study: cycling infrastructure, transportation programs and policies, and other environmental attributes. We focus our review on studies of utilitarian cycling (i.e. cycling for transportation, including commuting), as past research has demonstrated that utilitarian and recreational cycling are characterized by different patterns of behavior (Heesch et al., 2015; Heinen et al., 2010; Hoehner et al., 2005; Vernez-Moudon et al., 2005).

### 2.1. Cycling infrastructure

Infrastructure may encourage cycling by increasing awareness and raising visibility, enhancing convenience, improving perceived safety, and reducing conflict points with automobiles. Aggregate studies in Europe and the U.S. have found that cities with more extensive networks of bicycle lanes and paths have higher shares of bicycle commuting (Santos et al., 2013; Buehler and Pucher, 2011; Dill and Carr, 2003). Relatively few studies have analyzed this relationship at the disaggregate (i.e. individual) level, and the findings of these studies have often conflicted. For instance, Krizek and Johnson (2006) found that close proximity to on-street bicycle lanes, but not to off-street trails, was associated with cycling in Minneapolis and St. Paul, Minnesota. Vernez-Moudon et al. (2005) observed the opposite relationship in Seattle, Washington (i.e. cycling associated with off-street trails but not on-street lanes), while Winters et al. (2010a) found that neither type of infrastructure was associated with cycling in Vancouver, British Columbia.

The relative influences of different infrastructure types have also been examined in stated preference studies. This work has generally found that cyclists prefer at least some degree of physical separation from motorized traffic (Stinson and Bhat, 2003; Hunt and Abraham, 2007; Wardman et al., 2007), although debate still exists regarding the specific types of infrastructure and degree of separation that are most strongly associated with cycling. This discussion is further complicated by the influence of personal characteristics, as preferences for cycling infrastructure may vary with cycling experience (Hunt and Abraham, 2007) and gender (Garrard et al., 2008).

Fewer studies have considered the role of trip-end facilities such as bicycle parking and showers (Pucher et al., 2010b), although this type of infrastructure may be especially important for commute trips. Heinen et al. (2013) found that Dutch commuters were more likely to cycle to work if they had access to indoor bicycle parking at their destination, and Buehler (2012) similarly found bicycle parking and showers to be important factors in the decision to commute by bicycle in Washington, D.C. Hunt and Abraham (2007) analyzed this relationship using a stated preference survey, estimating that secure bicycle parking at destinations would have the same utility as a decrease of 26.5 minutes in time spent cycling in mixed traffic. These findings suggest that trip-end infrastructure may be a strong facilitator of bicycle commuting.

The relationship between infrastructure and cycling behavior is subject to several additional complexities that are worth noting and accounting for in mode choice analyses. First, the impacts of infrastructure and other environmental attributes near home, near work, and along the travel route may vary (Winters et al., 2010a), suggesting that the environment should be separately measured around these three spatial zones. Second, stated preference research has found that cyclists prefer continuous infrastructure (Stinson and Bhat, 2003), indicating the value of measuring not just the extent of the bicycle net-

work but also its connectivity. Finally, prior research has revealed the importance of accounting for both self-reported and objective measures of cycling infrastructure. Dill and Voros (2007) found that while objective measures of bicycle lane availability were not associated with utilitarian cycling in Portland, Oregon, *perceptions* of the availability of bicycle lanes played a significant role. Hoehner et al. (2005) similarly found that cycling for transportation in two U.S. cities was associated with the perception that bicycle lanes were present along most streets, but not with the objective measure of this characteristic. These results mirror a broader literature suggesting that perceptions of the built environment play a significant role in explaining behavior independent of objective measures of the same characteristics (McGinn et al., 2007), attesting to the importance of considering both self-reported and objective measures in mode choice analyses.

## 2.2. Transportation programs and policies

Program and policy interventions may serve as important complements to infrastructure investments (Pucher et al., 2010b). Several recent studies have examined changes in cycling behavior in cities that have combined infrastructure, program, and policy strategies, generally finding positive effects. Keall et al. (2015) used a quasi-experimental longitudinal research design to evaluate New Zealand's Model Communities Programme (MCP), which combines cycling-supportive infrastructure investments with community-wide promotion and awareness campaigns. The authors observed a 37% increase in walking and cycling in two MCP towns relative to control sites. Using longitudinal census data, Caulfield (2014) demonstrated that rates of cycling increased in Dublin after the city invested in infrastructure, a bicycle sharing program, speed limit reductions, and a bicycle purchasing assistance program. Other work has evaluated the Connect2 project in the United Kingdom, finding that proximity to funded facilities was associated with increases in walking and cycling two years after implementation (Goodman et al., 2014). Goodman et al. (2013) also recorded increases in bicycle commuting among 18 Cycling Demonstration Towns in England, which simultaneously invested in infrastructure and cycling training. Taken together, these longitudinal evaluations suggest that coordinated infrastructure, program, and policy interventions may facilitate changes in cycling behavior.

While the aforementioned studies examined coordinated packages of interventions, others have examined the impacts of specific strategies such as bicycle sharing and travel demand management (TDM) programs. Although the impacts of bicycle sharing programs are difficult to evaluate due to frequent coincidence with improvements to cycling infrastructure (Pucher et al., 2010b), several studies have found bicycle sharing programs in European and North American cities to be correlated with increases in cycling mode share (Fishman, 2015; Nadal, 2007; Beroud, 2010; Fuller et al., 2011, 2013). From the TDM perspective, Wardman et al. (2007) estimated that provision of financial incentives to commuters in Great Britain would have a much stronger effect on cycling than universal provision of separated cycling paths. Heinen et al. (2013) found that provision of a free public transport pass to employees was inversely associated with cycling to work in four Dutch municipalities, suggesting that employer-based incentives to reduce vehicle commuting may sometimes work to the detriment of cycling. Buehler (2012), however, found that employer-based public transport incentives were not associated with lower levels of cycling to work.

## 2.3. Other environmental attributes

Built environment characteristics such as density, land use mix, and street connectivity influence the distances between origins and destinations of travel and thus the time and monetary costs of traveling by different modes (Boarnet and Crane, 2001; Cervero, 2002; Rodriguez et al., 2006). Including these factors in mode choice models is therefore important to avoid misinterpreting the influence of travel time and cost variables, which are in part a function of built environment attributes (Rodriguez and Joo, 2004; Boarnet and Crane, 2001; Cervero, 2002). More broadly, the built environment may influence factors such as safety, pleasantness, and social interaction while traveling (LaJeunesse and Rodriguez, 2012), further illustrating the importance of including built environment measures in studies of cycling behavior.

Although research on the built environment and travel behavior has proliferated in recent years, much of this work has focused on driving and walking with comparatively few studies of cycling behavior (Fraser and Lock, 2010; Ewing and Cervero, 2010). Among studies that have focused on cycling, several have recorded significant or near-significant coefficients for density, land use mix, or street connectivity (Winters et al., 2010a; Kitamura et al., 1997; Rodriguez and Joo, 2004; Cervero and Duncan, 2003; Parkin et al., 2008; Rietveld and Daniel, 2004; Hoehner et al., 2005; Wendel-Vos et al., 2004; Dill and Voros, 2007). Multiple studies, however, have found attitudes and demographic characteristics to be much more strongly associated than the built environment with cycling behavior (Cervero and Duncan, 2003; Kitamura et al., 1997; Hoehner et al., 2005), suggesting that built environment interventions may be an important but ultimately insufficient approach to promoting cycling.

Features of the natural environment, such as topography, may also influence cycling mode choice. While greater slope is often assumed to be a deterrent to cycling, the evidence is not entirely straightforward: some studies have found hilly terrain to have a negative influence on cycling (Parkin et al., 2008; Winters et al., 2010a; Rodriguez and Joo, 2004; Rietveld and Daniel, 2004), while others have suggested that cyclists may prefer moderately sloping routes due to greater exercise benefits and the potential for rest periods while traveling downhill (Stinson and Bhat, 2003). Although topography is beyond the direct control of planners and policy makers, understanding its influence can inform policies and infrastructure investments

related to cycling; for instance, public transport integration strategies and the placement and design of cycling infrastructure may lessen the impacts of hilly terrain (Dill and Voros, 2007).

In summary, while previous literature has suggested a variety of ways in which planning and policy factors may influence the attractiveness of cycling relative to other travel modes, the evidence base has been mixed and several questions remain unresolved. In particular, there is a continued need for disaggregate studies that consider the relative importance of different types of investments and the potential role of the built environment. We respond to this need by modeling travel mode choice among commuters in Barcelona, incorporating several methodological nuances—including self-reported and objective measures and multiple spatial zones of analysis—that have been identified as important in past research on cycling behavior.

### 3. Methods

#### 3.1. Travel survey data

We used data from a travel behavior survey developed as part of the Transportation, Air Pollution, and Physical Activities (TAPAS) project, which aimed to comprehensively investigate the risks and benefits of cycling in Barcelona. The TAPAS survey was designed to assess the potential for built environment, policy, and programmatic interventions to increase active transportation in the city.

We recruited and surveyed study participants between June 2011 and May 2012. We chose on-street recruitment in order to identify commuters by travel mode and over-represent cyclists for adequate statistical power, given the relatively low mode share of cycling in Barcelona. Adult cyclists and non-cyclists were recruited from four possible sampling points within each of the ten city districts across Barcelona (for a total of 40 sampling points; Fig. 1). These sampling points were randomly selected within each of the ten districts to ensure adequate geographic coverage. We recruited participants at specific locations—including bicycle, car, and motorbike parking sites, *Bicing* stations, public transport stops, traffic lights, and street crossings—in the vicinity of each sampling point. Each location was sampled by three trained interviewers during the morning commute (7:45–11:30 a.m.) on four days within a randomly selected week. Cyclists were preferentially approached in order to increase their representation in the sample, and attempts were made to recruit a non-cyclist for every cyclist approached. Eligible participants were required to be between the ages of 18 and 65; to both live and work or attend school (e.g., college, university) within the municipality of Barcelona; and to be in sufficient self-reported health to ride a bicycle for 20 minutes. Additionally, individuals who lived within a ten-minute walk of their work or school location and those who commuted only by foot were excluded from the sampling framework, as cycling was the primary active travel mode of interest for this study.

After eligible participants were recruited in the street, they were called by trained interviewers to complete the survey via telephone with CATI. In addition to basic sociodemographic information, respondents were asked to describe their typical morning commute from home to work or school (hereafter referred to as “work”), including home and work addresses, all modes of transportation used in sequence, travel time for each mode, and combined weekly out-of-pocket expenses for this commute trip. Respondents reported whether bicycle lanes were present along at least two-thirds of their commute route and whether their employer or school provided incentives not to commute by private vehicle. Additionally, respondents reported whether there were *Bicing* stations in proximity to their home and work locations and whether they found the program to be difficult to use due to uncertainty in finding available bicycles or docking stations, problems that have been identified anecdotally in other bicycle sharing programs (Fishman et al., 2012; Flegenheimer, 2013).

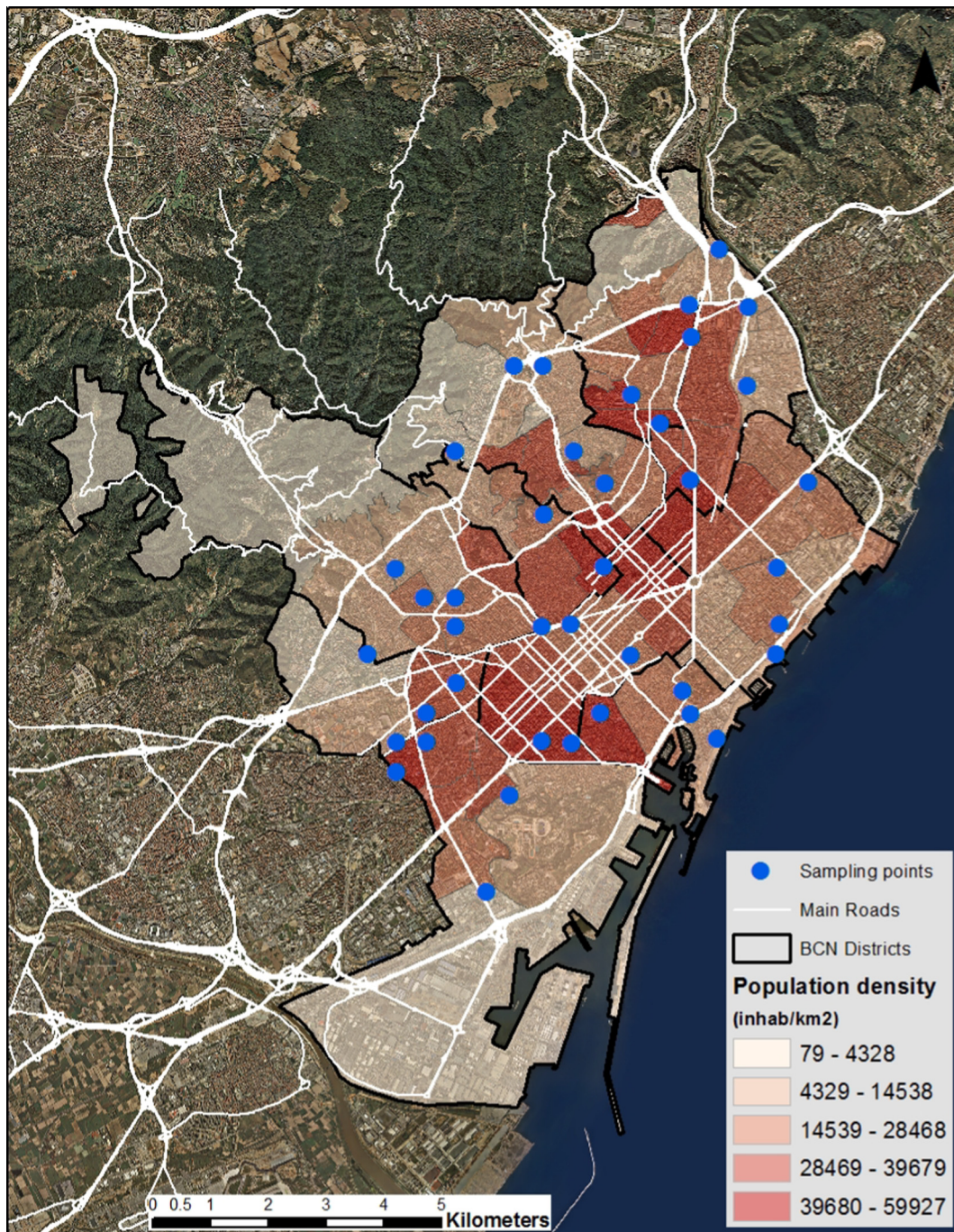
Respondents were classified as cyclists if their typical morning commute trip included at least ten continuous minutes of cycling by either *Bicing* or personal bicycle. To establish a framework for the mode choice analysis, cyclists were also asked to estimate the travel time and weekly costs associated with the “next best” mode or combination of modes that they would have selected if cycling were not available, while non-cyclists were asked to report estimated travel time and weekly costs if they were to use *Bicing* or a personal bicycle for their commute trip (either exclusively or in combination with other travel modes). This set of questions for the hypothetical commute trip created a contrast between attributes of the trip actually chosen and an available alternative that was not selected.

To address non-response on several key survey questions, we conducted multiple imputation using fully conditional specification (FCS) in Stata version 13.0. The FCS method allowed us to iteratively impute values for multiple variables (i.e. all variables with missing values) as a function of all other variables in the data set, using equations that recognized the different distributions and functional forms of different variable types (e.g., continuous, logit, ordered logit) (van Buuren et al., 2006). We performed ten imputations and combined the results using Rubin’s combination rules (Rubin, 1987).

#### 3.2. Objective environmental data

Objective measures of cycling infrastructure and other environmental attributes were created using a geographic information system (GIS). These variables were separately measured around a respondent’s home, work, and commute route, as these three spatial zones have been found to have distinct associations with cycling mode choice (Winters et al., 2010a). All home and work addresses were geocoded and environmental variables were measured within a 400-m circular buffer around each address, reflecting a distance that can be reasonably walked in five minutes at typical adult walking speeds





**Fig. 1.** Survey sampling points across city districts in the municipality of Barcelona.

(4.8 km/h). As participants did not directly describe their commute routes, ArcGIS Network Analyst was used to simulate the most likely route. This process involved determining the shortest-distance path between home and work with a priority on selecting streets with cycling infrastructure, based on research showing that cyclists are generally willing to deviate from the most direct route to travel on dedicated facilities or streets with low volumes of motor vehicle traffic (Winters et al., 2010b; Dill and Gliebe, 2008; Transport for London, 2012; Hunt and Abraham, 2007; Tilahun et al., 2007). Specifically, streets with bicycle lanes or paths were considered to be half of their true distance (i.e. distance “discount” of 50%), and the network calculation assumed this discounted distance in simulating the commute route. We conducted sensitivity analyses with other distance discount values ranging from 0% (i.e. no discount) to 90%, but the selected approach provided the most reasonable results (e.g., no unreasonably long detours) based on knowledge of the city and visual assessment of a subset of routes.

The objective environmental measures created for this analysis are listed in Table 1 and further defined in Table 2. Cycling infrastructure variables included the percentage of streets with bicycle lanes or paths, connectivity of the cycling network (i.e. density of intersections (1) that have three or more legs and (2) where at least one of the three legs is a “bicycle friendly” street (i.e. street with bicycle lanes or low motor vehicle traffic)), counts of *Bicing* stations, and counts of public bicycle parking racks. While the focus of this analysis was on cycling, counts of public transport stops were also included to assess potential competition with public transport modes. Other environmental attributes included the percentage of the simulated commute route with a slope greater than three percent and three measures of the built environment: population density, land use mix, and commercial intensity. Population density was measured as persons per square kilometer. Land use mix was calculated based on the number and relative square meters of nine land uses (residential, commercial, office, education, health, bars, sport, religion, leisure), combined into a single measure using the methodology outlined by Frank et al. (2006). Commercial intensity—a measure of destination activity—was measured from municipal tax records as the percentage of land area in non-residential use.

While the majority of sociodemographic variables were measured at the individual level through the travel survey, we also included a measure of neighborhood socioeconomic status (SES). This measure was a deprivation index developed for five Spanish cities, including Barcelona, as part of the MEDEA Project. The MEDEA index was created using principal components analysis of the following five socioeconomic indicators (all measured with 2001 census data at the tract level): unemployment, part-time workers, manual workers, under-educated population (all), and under-educated population (young adults) (Domínguez-Berjón et al., 2008).

All objective environmental variables were measured for the home and work buffers, with the exception of neighborhood SES (home only) and bicycle parking racks (work only). The latter modeling choice followed past research that has focused on parking facilities at work (Pucher et al., 2010b; Heinen et al., 2013; Buehler, 2012; Hunt and Abraham, 2007); we also tested a measure of bicycle parking at the home location in preliminary analyses, but this measure was not significant and did not affect the overall pattern of results, and thus was not considered further. The only environmental variables measured along the commute route were topography, bicycle lanes, and bicycle network connectivity, as the remaining variables were presumed to be of limited relevance to the commute environment. Among the route-level variables, topography and bicycle lane presence were measured for the streets comprising the simulated commute route, while bicycle network connectivity was measured within a “rectangle-by-area” buffer representing the smallest rectangle enclosing the entire simulated route.

### 3.3. Conceptual approach and empirical analysis

For this analysis, we modeled the dichotomous choice between cycling (i.e. a commute trip that included either *Bicing* or personal bicycle) versus a non-cycling alternative (i.e. a commute trip that did not include cycling). This choice was set up using the travel survey responses about actual and hypothetical commute trips. As described in Section 3.1, survey respondents reported the travel time and weekly costs for their *actual* commute trip as well as for a *hypothetical* commute trip that they did not take. For cyclists, this hypothetical trip was the “next best” mode or set of modes that they would have selected if cycling were not available; for non-cyclists, the hypothetical trip was one that included cycling (either *Bicing* or a personal bicycle). Thus, each individual’s dichotomous choice set included cycling, but the non-cycling alternative varied across respondents.

We modeled this choice using random utility theory, in which individuals are assumed to select the alternative that yields the highest utility. Utility is defined as having an observable systematic component and a stochastic component that is independent and identically Gumbel-distributed. Following past work and the literature review findings outlined in Section 2, we assumed that the utility of each mode for a given traveler—and thus the propensity to commute by bicycle—depended on

**Table 1**  
Objective environmental variables by level(s) of measurement.

| Variable                              | Level(s) of measurement |       |      |
|---------------------------------------|-------------------------|-------|------|
|                                       | Home                    | Route | Work |
| <i>Cycling infrastructure</i>         |                         |       |      |
| Bicycle lanes <sup>a</sup>            | X                       | X     | X    |
| Bicycle network connectivity          | X                       | X     | X    |
| Bicycle parking                       |                         |       | X    |
| <i>Bicing availability</i>            |                         |       |      |
| Bicing stations <sup>a</sup>          | X                       |       | X    |
| <i>Other environmental attributes</i> |                         |       |      |
| Topography (slope)                    |                         | X     |      |
| Population density                    | X                       |       | X    |
| Commercial intensity                  | X                       |       | X    |
| Land use mix                          | X                       |       | X    |
| Public transport stops                | X                       |       | X    |
| Neighborhood SES                      | X                       |       |      |

SES = socioeconomic status.

<sup>a</sup> Denotes variables that were also self-reported in the travel survey.



**Table 2**Descriptive statistics for study sample ( $n = 765$ )<sup>a</sup>.

| Variable                                       | Description  | Mean or % <sup>b</sup> | SD    | Min.  | Max.   |
|--|--|------------------------|-------|-------|--------|
| <i>Commute trip attributes</i>                 |  |                        |       |       |        |
| Distance                                       | Network distance between home and work, in kilometers  | 3.83                   | 2.01  | 0.42  | 14.56  |
| Cost   | Total weekly out-of-pocket expenses for typical commute trip, in Euros   | 5.57                   | 8.38  | 0.00  | 96.00  |
| Time   | Total travel time for typical commute trip, in hours   | 0.40                   | 0.20  | 0.03  | 1.33   |
| <i>Sociodemographic characteristics</i>        |  |                        |       |       |        |
| Gender   | Percent female   | 51.90                  | —     | —     | —      |
| Age  | Age, in years  | 36.39                  | 10.26 | 18.00 | 65.00  |
| Children                                       | Percent with children in household   | 35.56                  | 0.48  | 0.00  | 1.00   |
| Income   | Scaled monthly household income, in Euros (% in each category):  |                        |       |       |        |
|  | Less than 1,000  | 7.20                   | —     | —     | —      |
|  | 1000–1999  | 32.16                  | —     | —     | —      |
|  | 2000–2999  | 27.73                  | —     | —     | —      |
|  | 3000–3999  | 19.31                  | —     | —     | —      |
|  | 4000–4999  | 8.71                   | —     | —     | —      |
|  | 5000 or more   | 4.90                   | —     | —     | —      |
| College education                              | Percent with education beyond high school  | 69.80                  | —     | —     | —      |
| Vehicle ownership                              | Percent that own at least one car  | 64.77                  | —     | —     | —      |
| Neighborhood SES                               | Neighborhood deprivation (MEDEA index; lower/negative values = higher SES)   | −0.13                  | 0.88  | −1.76 | 3.03   |
| <i>Policies</i>                                |  |                        |       |       |        |
| Incentive                                      | Percent reporting an employer-based incentive not to drive to work   | 4.84                   | —     | —     | —      |
| <i>Self-reported measures</i>                  |  |                        |       |       |        |
| Bicycle lanes – route                          | Percent reporting bicycle lanes along at least two-thirds of commute route   | 54.26                  | —     | —     | —      |
| <i>Bicing stations – home</i>                  |  |                        |       |       |        |
|  | Bicing station within walking distance of home (% in each category):   |                        |       |       |        |
|  | Totally disagree   | 3.86                   | —     | —     | —      |
|  | Disagree   | 7.06                   | —     | —     | —      |
|  | Agree  | 59.05                  | —     | —     | —      |
|  | Totally agree  | 30.04                  | —     | —     | —      |
| <i>Bicing stations – work</i>                  |  |                        |       |       |        |
|  | Bicing station within walking distance of work or school (% in each category):   |                        |       |       |        |
|  | Totally disagree   | 2.38                   | —     | —     | —      |
|  | Disagree   | 10.31                  | —     | —     | —      |
|  | Agree  | 63.56                  | —     | —     | —      |
|  | Totally agree  | 23.75                  | —     | —     | —      |
| <i>Bicing uncertainty</i>                      |  |                        |       |       |        |
|  | Uncertainty in finding available Bicing bicycles or parking docks (% in each category):  |                        |       |       |        |
|  | Totally disagree   | 1.39                   | —     | —     | —      |
|  | Disagree   | 33.74                  | —     | —     | —      |
|  | Agree  | 50.55                  | —     | —     | —      |
|  | Totally agree  | 14.33                  | —     | —     | —      |
| <i>Objective measures within 400 m of home</i> |  |                        |       |       |        |
| Bicing stations                                | Count of Bicing stations   | 4.27                   | 2.54  | 0.00  | 13.00  |
| Bicycle lanes                                  | Percent of streets with bicycle lanes (includes separated and not separated)   | 13.93                  | 13.39 | 0.00  | 53.76  |
| Bicycle network connectivity                   | Number of intersections that (1) have 3 or more legs and (2) where at least one of the three legs is “bicycle friendly” (bicycle lanes or low traffic) | 54.96                  | 26.70 | 0.00  | 190.52 |
| Public transport stops                         | Count of public transport stops  | 17.24                  | 5.39  | 4.00  | 40.00  |
| Population density                             | Population density (persons/km <sup>2</sup> ), in tens of thousands  | 2.96                   | 1.20  | 0.04  | 5.77   |
| Commercial intensity                           | Percent of land area in non-residential use <sup>c</sup>   | 54.85                  | 26.41 | 1.07  | 139.73 |
| Land use mix                                   | Land use mix (based on number and relative square meters of nine land uses)  | −0.25                  | 0.19  | −0.71 | 0.22   |
| <i>Objective measures along commute route</i>  |  |                        |       |       |        |
| Bicycle lanes                                  | Percent of streets with bicycle lanes (includes separated and not separated)   | 71.84                  | 24.41 | 0.00  | 100.00 |
| Bicycle network connectivity                   | Number of intersections that (1) have 3 or more legs and (2) where at least one of the three legs is “bicycle friendly” (bicycle lanes or low traffic) | 51.67                  | 19.63 | 12.67 | 165.51 |
| Slope  | Percent of route with slope greater than 3%  | 0.10                   | 0.43  | 0.00  | 4.95   |
| <i>Objective measures within 400 m of work</i> |  |                        |       |       |        |
| Bicing stations                                | Count of Bicing stations   | 4.98                   | 3.10  | 0.00  | 15.00  |
| Bicycle lanes                                  | Percent of streets with bicycle lanes (includes separated and not separated)   | 17.99                  | 13.72 | 0.00  | 100.00 |
| Bicycle network connectivity                   | Number of intersections that (1) have 3 or more legs and (2) where at least one of the three legs is “bicycle friendly” (bicycle lanes or low traffic) | 48.82                  | 31.67 | 0.00  | 191.11 |
| Bicycle parking                                | Count of public bicycle racks  | 26.26                  | 16.65 | 0.00  | 62.00  |
| Public transport stops                         | Count of public transport stops  | 18.27                  | 7.08  | 2.00  | 48.00  |
| Population density                             | Population density (persons/km <sup>2</sup> ), in tens of thousands  | 2.47                   | 1.16  | 0.01  | 5.98   |
| Commercial intensity                           | Percent of land area in non-residential use <sup>c</sup>   | 69.77                  | 32.70 | 1.94  | 139.73 |
| Land use mix                                   | Land use mix (based on number and relative square meters of nine land uses)  | −0.33                  | 0.18  | −0.71 | 0.24   |

SD = standard deviation, SES = socioeconomic status.

<sup>a</sup> All values averaged across ten imputed data sets.<sup>b</sup> SD, minimum, and maximum values not meaningful for individual-level variables reported as percentages.<sup>c</sup> Values may exceed 100% due to multiple floors of commercial use.



general trip attributes (distance, out-of-pocket costs, travel time); sociodemographic characteristics of the traveler; availability of incentives not to commute by private vehicle; and self-reported and objectively measured infrastructure and environmental characteristics near home, near work, and along the commute route.

The parameters of this utility function were estimated using conditional logistic regression following the approach originally outlined by McFadden (1974). Under this approach, the utility of each mode is modeled as a function of *mode-specific variables* that vary both across respondents and across modes for any given respondent (e.g., travel time); and *respondent-specific variables* that vary across respondents but are fixed across modes for an individual respondent (e.g., sociodemographic characteristics). The regression model for a scenario with  $J$  modes,  $p$  mode-specific variables, and  $q$  respondent-specific variables can be specified as follows:

$$u_i = \mathbf{X}_i\beta + (\mathbf{z}_i\mathbf{A})' + \epsilon_i$$

where  $\mathbf{X}_i$  is a  $J \times p$  matrix of mode-specific variables for respondent  $i$ ;  $\mathbf{z}_i$  is a  $1 \times q$  vector of respondent-specific variables for respondent  $i$ ;  $\beta$  and  $\mathbf{A}$  are vectors of mode-specific and respondent-specific regression coefficients, respectively;  $\epsilon_i$  is a  $J \times 1$  vector of Gumbel-distributed error terms for respondent  $i$  by mode; and  $u_i$  is a vector quantifying the utility provided to respondent  $i$  by the  $J$  modes. Individuals are assumed to select the mode  $j$  that maximizes the specified utility function.

In our model, out-of-pocket costs and travel time were designated as *mode-specific variables* because these characteristics varied across modes for any given respondent. Given the potential for trip costs and travel time to separately influence the disutility of each mode, separate cost and time variables were constructed for cycling and non-cycling commute trips to allow the coefficients for these two factors to vary by mode. Trip distance, sociodemographic characteristics, travel demand incentives, and infrastructure and environmental attributes were *respondent-specific variables*, as these factors did not vary by travel mode for a given respondent; these variables were therefore interacted with the cycling alternative to identify their effect. As a result, the coefficients for these variables represent the association of each variable with the propensity to commute by bicycle versus all other modes.

Four versions of this general model were estimated. General trip attributes (i.e. distance, out-of-pocket costs, travel time), sociodemographic characteristics, and the availability of travel demand incentives were included in a baseline model (Model 0) and all subsequent regressions. In Model A, self-reported (i.e. reported by respondents) measures of cycling infrastructure were added to the baseline regression. Model B was specified to include all objective environmental measures, omitting self-reported measures of cycling infrastructure. In the final model (Model C), both self-reported and objectively measured environmental attributes were analyzed.

### 3.4. Additional analyses

We conducted a series of additional analyses to further explore the regression results. First, we compared the statistical fit of the four models using McFadden's adjusted  $R^2$  values and alternative-specific constants for cycling. These comparisons, combined with an assessment of the correlation between self-reported and GIS-based measures of similar environmental constructs, allowed us to consider the relative explanatory power of self-reported and objective environmental measures.

Next, we calculated point elasticities (for continuous independent variables) and percent change values (for binary and categorical independent variables) to assess the relative importance of selected explanatory variables that are relevant to planning and policy intervention. Point elasticities measured the percent change in the probability of cycling given a percent change in the attribute of interest. For each selected continuous variable, we calculated disaggregate elasticities across all individual respondents and averaged these values to derive a sample mean. As suggested by Hensher et al. (2005), prior to averaging, the elasticity values were weighted by the initial predicted probability of cycling from our final regression model; this provided greater weight to individuals who had a higher baseline probability of cycling and less weight to individuals with a lower predicted probability.

For selected binary variables, we calculated the percent change in the predicted probability of commuting by bicycle when responses were shifted from "yes" to "no" and vice versa. For categorical variables measured on a Likert scale, we estimated the percent change associated with a one-level increase in the scaled response. As with the point elasticities, we derived a sample mean from disaggregate values across all individuals after weighting individual estimates by the initial predicted probability of commuting by bicycle.

Finally, given that the variables explaining cycling may differ for *Bicing* users and other (non-*Bicing*) cyclists, we re-estimated the regression models excluding those who commuted by personal bicycle. This approach allowed us to test the sensitivity of our results to the particular form of cycling selected.

## 4. Results

Between June 2011 and May 2012, 18,469 commuters were approached across the 40 sampling points displayed in Fig. 1. Of these commuters, 6701 agreed to answer initial screening questions, 1406 met the eligibility criteria, and 809 completed the travel survey. Among these 809 individuals, 23 were excluded from the final sample because they did not select cycling as either their actual or their hypothetical commute mode and 21 were excluded because they did not provide home or work addresses that could be accurately geocoded. This led to a final sample of  $n = 765$ .

Among these participants, 311 had missing (non-response) values for one or more survey variables considered in the final regression models; non-response was most common for income (24% missing), vehicle ownership (12% missing), uncertainty in finding available *Bicing* bicycles and docking stations (4% missing), and weekly costs of the actual and hypothetical commute modes (4% and 3% missing, respectively). Incomplete cases were found to be significantly different from complete cases on the majority of regression variables (results not shown). Thus, we conducted multiple imputation as described in Section 3.1 to impute all missing values and retain the full sample of 765 participants.

Descriptive statistics for the study sample ( $n = 765$ ) are presented in Table 2. The mean commute distance for our sample was 3.83 km, which generally corresponds with citywide surveys of larger, population-based samples in Barcelona. For instance, the average commute distance in the municipality of Barcelona was found to be 4.20 km in a 2008 citywide daily mobility survey (Autoritat del Transport Metropolità, 2008); the slightly smaller value for our sample reflects the over-representation of cyclists, who tend to take shorter trips.

Just less than half of the study sample (47%,  $n = 361$ : “cyclists”) reported using *Bicing* or a personal bicycle as part of their typical commute, while 53% ( $n = 404$ : “non-cyclists”) relied entirely upon other modes of transportation. One-third of participants (23% of cyclists, 43% of non-cyclists) combined two or more travel modes for their typical commute (data not shown). The mode share of cycling illustrates the over-representation of cyclists in this study, an approach that was selected to provide sufficient statistical power for drawing comparisons between cycling and non-cycling modes in a city with a relatively low share of bicycle commuting. Despite this sampling approach, the sociodemographic characteristics of the sample are similar to those of Barcelona city residents in general (Appendix A Table A1). These similarities, which may reflect the citywide distribution of survey recruitment points, suggest that generalizations from the study sample to the larger population of Barcelona may be supported despite the non-random process used to recruit participants.

Among non-cyclists, 64% traveled primarily (i.e. greatest proportion of travel time) by public transport modes while only 5% traveled primarily by car (Table 3). This modal split, particularly the low share of car commuting, reflects the focus of this study on the municipality of Barcelona. When cyclists were asked to describe the mode or combination of modes that they would use if cycling were not available, the majority (59%) reported that they would commute primarily by public transport, 35% would commute primarily by walking, and 5% would commute primarily by car or motorbike (Table 3).

The conditional logistic regression results for the baseline (Model 0), self-reported (Model A), objective (Model B), and combined (Model C) models are summarized in Table 4. As previously described in Section 3.3, the coefficients in these models indicate each variable's association with the propensity to commute by bicycle versus all other modes (with the exception of costs and travel time, which have separate coefficients for cycling and non-cycling modes). The adjusted McFadden's  $R^2$  values for the four models range from 0.18 to 0.23; while somewhat low, these measures of statistical fit are consistent with the range demonstrated in past cycling mode choice analyses (Hensher et al., 2005).

Travel time, distance, and costs were included as general trip attributes in all four models. Travel time and distance were inversely associated with bicycle commuting, and the disutility of time spent traveling was comparable for cycling and non-cycling modes. Similar results were obtained when separate measures of in- and out-of-vehicle travel time were modeled, although the coefficient on travel distance was smaller in absolute value under this specification (results not shown). In contrast, the coefficients for cost varied by mode: while combined out-of-pocket trip expenses for cycling were not associated with bicycle commuting, the cost of traveling by non-cycling modes was positively associated with the decision to travel by those modes.

Sociodemographic characteristics were also included in all four models. Females were consistently less likely than males to commute by bicycle, corresponding with past research that has found cycling to be less prevalent among women (Heinen et al.,

**Table 3**  
Modes actually used by non-cyclists ( $n = 404$ ) and hypothetical modes selected by cyclists ( $n = 361$ )<sup>a</sup>.

| Mode      | Mode actually used by non-cyclists ( $n = 404$ ) |       | Hypothetical mode selected by cyclists ( $n = 361$ ) |       |
|-----------|--|-------|--|-------|
|           | N  | %     | N  | %     |
| Car       | 20   | 4.95  | 9  | 2.49  |
| Motorbike | 101  | 25.00 | 8  | 2.22  |
| Metro     | 121  | 29.95 | 128  | 35.46 |
| Bus       | 123  | 30.45 | 71   | 19.67 |
| Train     | 8  | 1.98  | 9  | 2.49  |
| Tram      | 5  | 1.24  | 3  | 0.83  |
| Walking   | 26 <sup>b</sup>                                  | 6.44  | 127  | 35.18 |
| Other     | 0  | 0.00  | 6  | 1.66  |

<sup>a</sup> When multiple modes were used for the actual or hypothetical commute trip, respondents were classified by the mode in which they spent the greatest amount of travel time; 43% of non-cyclists combined two or more modes for their actual commute trip, and 41% of cyclists reported that they would combine two or more modes for their hypothetical non-cycling trip.

<sup>b</sup> Although walk-only commuters were excluded from the sampling frame, individuals who walked for a portion of their commute trip were not excluded; thus, some respondents are classified as walkers in this table because walking was the most time-intensive, though not the only, mode used for their trip.

**Table 4**

Associations of trip attributes, sociodemographics, policies, and self-reported and objective environmental characteristics with propensity to commute by bicycle ( $n = 765$ )<sup>a</sup>.

|  | Model O: Baseline        |       | Model A: Self-report     |       | Model B: Objective       |       | Model C: Combined        |       |
|--|--------------------------|-------|--------------------------|-------|--------------------------|-------|--------------------------|-------|
|  | Coefficient <sup>b</sup> | SE    | Coefficient <sup>b</sup> | SE    | Coefficient <sup>b</sup> | SE    | Coefficient <sup>b</sup> | SE    |
| <i>Mode-specific trip attributes</i>           |                          |       |                          |       |                          |       |                          |       |
| Cycling constant (ASC)                         | 2.270***                 | 0.523 | 0.240                    | 1.338 | 2.991**                  | 1.205 | 1.527                    | 1.750 |
| Cost – cycling                                 | 0.004                    | 0.014 | 0.010                    | 0.015 | –0.002                   | 0.015 | 0.006                    | 0.016 |
| Cost – all other modes                         | 0.130***                 | 0.026 | 0.140***                 | 0.027 | 0.134***                 | 0.027 | 0.143***                 | 0.029 |
| Travel time – cycling                          | –4.089***                | 0.640 | –4.160***                | 0.675 | –4.070***                | 0.675 | –4.295***                | 0.701 |
| Travel time – all other modes                  | –3.415***                | 0.519 | –3.535***                | 0.554 | –3.548***                | 0.548 | –3.678***                | 0.579 |
| <i>Respondent-specific trip attributes</i>     |                          |       |                          |       |                          |       |                          |       |
| Trip distance                                  | –0.147**                 | 0.068 | –0.141*                  | 0.072 | –0.148*                  | 0.080 | –0.135                   | 0.083 |
| <i>Sociodemographics</i>                       |                          |       |                          |       |                          |       |                          |       |
| Female   | –0.718***                | 0.180 | –0.710***                | 0.191 | –0.802***                | 0.191 | –0.805***                | 0.201 |
| Age  | –0.006                   | 0.009 | –0.010                   | 0.009 | –0.015                   | 0.010 | –0.019*                  | 0.010 |
| Income (ref = less than 1000€)                 |                          |       |                          |       |                          |       |                          |       |
| 1000–1999€                                     | –0.150                   | 0.390 | –0.328                   | 0.417 | –0.157                   | 0.419 | –0.271                   | 0.427 |
| 2000–2999€                                     | –0.552                   | 0.391 | –0.741*                  | 0.411 | –0.694                   | 0.426 | –0.792*                  | 0.440 |
| 3000–3999€                                     | –0.496                   | 0.433 | –0.699                   | 0.446 | –0.663                   | 0.464 | –0.735                   | 0.474 |
| 4000–4999€                                     | –0.468                   | 0.492 | –0.738                   | 0.520 | –0.573                   | 0.537 | –0.698                   | 0.569 |
| ≥ 5000€  | –0.892                   | 0.590 | –1.128*                  | 0.623 | –1.197*                  | 0.622 | –1.171*                  | 0.660 |
| College education                              | 0.597***                 | 0.195 | 0.639***                 | 0.206 | 0.625***                 | 0.207 | 0.657***                 | 0.217 |
| Vehicle ownership                              | –0.203                   | 0.220 | –0.103                   | 0.234 | –0.194                   | 0.234 | –0.121                   | 0.245 |
| Children                                       | 0.118                    | 0.193 | 0.137                    | 0.204 | 0.206                    | 0.203 | 0.182                    | 0.214 |
| Neighborhood SES                               | –0.025                   | 0.108 | –0.015                   | 0.114 | –0.198                   | 0.136 | –0.209                   | 0.144 |
| <i>Policies</i>                                |                          |       |                          |       |                          |       |                          |       |
| Incentive <sup>c</sup>                         | –0.768*                  | 0.421 | –0.850*                  | 0.456 | –0.672                   | 0.449 | –0.736                   | 0.483 |
| <i>Self-reported measures</i>                  |                          |       |                          |       |                          |       |                          |       |
| Bicycle lanes along route (1 = yes, 0 = no)    |                          |       | 0.561***                 | 0.189 |                          |       | 0.632***                 | 0.220 |
| Bicing stations, home (ref = totally disagree) |                          |       |                          |       |                          |       |                          |       |
| Disagree                                       |                          |       | 1.718**                  | 0.847 |                          |       | 1.836**                  | 0.876 |
| Agree  |                          |       | 1.632**                  | 0.792 |                          |       | 1.593*                   | 0.825 |
| Totally agree                                  |                          |       | 2.103**                  | 0.805 |                          |       | 2.050**                  | 0.835 |
| Bicing stations, work (ref = totally disagree) |                          |       |                          |       |                          |       |                          |       |
| Disagree                                       |                          |       | –0.709                   | 0.749 |                          |       | –0.827                   | 0.791 |
| Agree  |                          |       | 0.260                    | 0.691 |                          |       | –0.039                   | 0.745 |
| Totally agree                                  |                          |       | 0.762                    | 0.715 |                          |       | 0.489                    | 0.766 |
| Bicing uncertainty (ref = totally disagree)    |                          |       |                          |       |                          |       |                          |       |
| Disagree                                       |                          |       | 0.153                    | 0.778 |                          |       | 0.391                    | 0.812 |
| Agree  |                          |       | –0.162                   | 0.775 |                          |       | 0.122                    | 0.806 |
| Totally agree                                  |                          |       | –0.253                   | 0.811 |                          |       | 0.010                    | 0.844 |
| <i>Objective measures (home)</i>               |                          |       |                          |       |                          |       |                          |       |
| Bicing stations                                |                          |       |                          |       | 0.090*                   | 0.051 | 0.047                    | 0.054 |
| Bicycle lanes                                  |                          |       |                          |       | 0.014                    | 0.010 | 0.014                    | 0.010 |
| Bicycle network connectivity                   |                          |       |                          |       | 0.008*                   | 0.005 | 0.010*                   | 0.005 |
| Public transport stops                         |                          |       |                          |       | –0.059***                | 0.019 | –0.050**                 | 0.019 |
| Population density                             |                          |       |                          |       | –0.109                   | 0.162 | –0.122                   | 0.172 |
| Commercial intensity                           |                          |       |                          |       | –0.007                   | 0.005 | –0.008                   | 0.005 |
| Land use mix                                   |                          |       |                          |       | 0.601                    | 0.998 | 0.463                    | 1.053 |
| <i>Objective measures (route)</i>              |                          |       |                          |       |                          |       |                          |       |
| Bicycle lanes                                  |                          |       |                          |       | –0.003                   | 0.005 | –0.008                   | 0.006 |
| Bicycle network connectivity                   |                          |       |                          |       | –0.017***                | 0.006 | –0.017***                | 0.006 |
| Slope greater than 3%                          |                          |       |                          |       | –0.549**                 | 0.267 | –0.538**                 | 0.273 |
| <i>Objective measures (work)</i>               |                          |       |                          |       |                          |       |                          |       |
| Bicing stations                                |                          |       |                          |       | 0.102**                  | 0.046 | 0.091*                   | 0.049 |
| Bicycle lanes                                  |                          |       |                          |       | 0.018*                   | 0.010 | 0.013                    | 0.010 |
| Bicycle network connectivity                   |                          |       |                          |       | 0.009**                  | 0.004 | 0.011**                  | 0.005 |
| Bicycle parking                                |                          |       |                          |       | –0.030**                 | 0.012 | –0.032**                 | 0.012 |
| Public transport stops                         |                          |       |                          |       | –0.009                   | 0.014 | –0.005                   | 0.015 |
| Population density                             |                          |       |                          |       | 0.211                    | 0.146 | 0.145                    | 0.155 |
| Commercial intensity                           |                          |       |                          |       | 0.004                    | 0.005 | 0.004                    | 0.005 |
| Land use mix                                   |                          |       |                          |       | –1.520*                  | 0.874 | –1.197                   | 0.920 |

Table 4 (continued)

|   | Model O: Baseline        |    | Model A: Self-report     |    | Model B: Objective       |    | Model C: Combined        |    |
|---|--------------------------|----|--------------------------|----|--------------------------|----|--------------------------|----|
|   | Coefficient <sup>b</sup> | SE | Coefficient <sup>b</sup> | SE | Coefficient <sup>b</sup> | SE | Coefficient <sup>b</sup> | SE |
| <i>Model fit statistics<sup>d</sup></i> |                          |    |                          |    |                          |    |                          |    |
| McFadden's $R^2$                        | 0.218                    |    | 0.277                    |    | 0.270                    |    | 0.312                    |    |
| McFadden's Adjusted $R^2$               | 0.184                    |    | 0.224                    |    | 0.202                    |    | 0.225                    |    |

SE = standard error, ASC = alternative-specific constant, SES = socioeconomic status.

<sup>a</sup> All coefficients and standard errors compiled across ten imputed data sets using Rubin's combination rules (Rubin, 1987).

<sup>b</sup> Coefficients indicate associations with the propensity to commute by bicycle versus all other modes (with the exception of costs and travel time, which have separate coefficients for cycling and non-cycling modes).

<sup>c</sup> Approximately half of participants reporting an employer-based travel demand incentive used public transport, suggesting that incentives were largely public transport-based.

<sup>d</sup> Reported fit statistics represent median values across ten imputed data sets.

\* Significant at 90% confidence.

\*\* Significant at 95% confidence.

\*\*\* Significant at 99% confidence.

2010). Age was inversely associated with bicycle commuting in one model (Model C), potentially reflecting the physical exertion of cycling. Education beyond high school was positively associated with cycling in all four models. Household income was inversely associated with bicycle commuting, but the pattern of statistical significance across income categories was inconsistent; this result should be interpreted with caution due to the use of imputed data (24% of values imputed for income). While vehicle ownership was expected to be an important predictor of bicycle commuting, this variable did not reach statistical significance in any of the regression models, possibly reflecting the low percentage of motor vehicle users in our urban sample.

Travel demand incentives were inversely associated with bicycle commuting in all four models, reaching statistical significance in Models A and C. This finding indicates that respondents whose schools or employers offered incentives not to commute by private vehicle were less likely to cycle to work.

Self-reported measures of bicycle lanes and *Bicing* access were included in Models A and C. In both models, self-reported presence of bicycle lanes along at least two-thirds of the commute route and self-reported access to *Bicing* stations near home were positively associated with bicycle commuting. Self-reported *Bicing* presence near work and uncertainty about *Bicing* capacity, on the other hand, were not associated with bicycle commuting in either model.

Objective measures of cycling infrastructure (i.e. *Bicing* stations, bicycle lanes, bicycle network connectivity, and public bicycle parking racks) were assessed in Models B and C. Counts of *Bicing* stations near home were positively associated with bicycle commuting in Model B, although this relationship was no longer significant after self-reported measures of *Bicing* access were added in Model C. Counts of *Bicing* stations near work were positively associated with cycling in both models. Bicycle lanes were positively associated with cycling when measured near work, but non-significant when measured near home and along the commute route; the coefficient for bicycle lanes near work, however, was no longer significant after accounting for self-reported availability of bicycle lanes in Model C. Measures of bicycle network connectivity at both home and work were positively associated with cycling in both models. An unexpected association, however, was found for the commute route: when measured at this level, bicycle network connectivity was inversely associated with cycling in both models. This result persisted when the route-level variables were interacted with trip distance (results not shown). The presence of public bicycle parking racks near work was inversely associated with cycling in both models.

Additional objective measures in Models B and C included public transport stops and land use characteristics. Counts of public transport stops near home were inversely associated with bicycle commuting in both models, but were not significant when measured near work. Land use mix was inversely associated with cycling in Model B, while population density and commercial intensity were not associated with cycling in either model.

## 5. Discussion

This analysis provided insight into factors that explain cycling mode choice among a sample of adult commuters in the municipality of Barcelona. The findings suggest that a variety of planning and policy factors—including cycling infrastructure, public transport availability, and travel demand incentives—are associated with the decision to commute by bicycle, with differences between self-reported and objective measures. The regression results and potential policy implications are discussed by variable type in the sections that follow.

### 5.1. General trip attributes

The inverse associations of cycling with travel time and distance are consistent with travel demand theory and past research (Heinen et al., 2013; Winters et al., 2010a; Parkin et al., 2008; Rietveld and Daniel, 2004; Frank et al., 2008). These results may reflect the opportunity cost of time spent commuting as well as the energy expenditure associated with cycling. Similarly, the negative coefficients for slope may reflect the physical exertion required to cycle on hilly terrain. While it may be reasonable to expect positive coefficients for distance, time, and slope within the context of cycling for health, the results



suggest that in the case of commute trips—for which timing and physical appearance are important considerations—these factors are deterrents to cycling. Additionally, cyclists in our sample were not more likely than non-cyclists to state that cycling would improve their personal health (data not shown), suggesting that health considerations were not particularly important factors in commute mode choice for our sample.

The results for out-of-pocket expenses initially seem counterintuitive, implying that as the cost of non-cycling modes increases, the propensity to select these modes also increases. This finding, however, is attributable to the sampling design for this study, in which cyclists were over-represented and attempts were made to recruit a non-cyclist for every cyclist in the sample. By virtue of this sampling design, approximately half of the respondents (cyclists) had low costs for the travel mode chosen (cycling), while the other half (non-cyclists) had a relatively high cost for the travel mode chosen (e.g., public transport, car). The latter group of non-cyclists therefore selected a more costly mode, and these respondents were then asked to compare their selected mode to a generally less costly alternative (cycling). This configuration made it appear as if cost had a positive association with mode selection for these respondents.

## 5.2. Measures of cycling infrastructure

Among the self-reported measures of cycling infrastructure included in this study, access to *Bicing* stations near home and to bicycle lanes along the commute route were consistently and positively associated with bicycle commuting. Although these findings may in part reflect a greater awareness of infrastructure availability among cyclists relative to users of other modes, they suggest that perceptions of cycling-supportive infrastructure are important factors in the decision to commute by bicycle. The self-reported measures also suggest that uncertainty about *Bicing* capacity (i.e. inability to find available bicycles and docking stations) was not a significant deterrent to bicycle commuting in our sample, despite anecdotal evidence of this program limitation.

Among the objective infrastructure measures, cycling was associated in the expected direction with *Bicing* stations (home and work), bicycle lanes (work only), and bicycle network connectivity (home and work). Two of these associations—*Bicing* stations near home and bicycle lanes near work—were no longer statistically significant after accounting for self-reported infrastructure measures, suggesting that perceived access to *Bicing* stations and bicycle lanes may have greater explanatory power than objective measures of access.

The results for *Bicing* station presence differ slightly from previous work with the TAPAS travel survey, which found that *Bicing* stations near home (but not near work) were positively associated with cycling (Cole-Hunter et al., 2015). This minor difference may be explained by different methodologies (e.g., the previous study modeled general propensity to commute by bicycle while the present study modeled the choice between two specific travel alternatives) and different sets of independent variables (e.g., the previous analysis focused on objective measures). These findings further illustrate the relevance of self-reported infrastructure measures.

While measures of bicycle network connectivity near home and near work were positively associated with cycling, an inverse association was found for bicycle connectivity along the commute route. While unanticipated, this finding could imply that lower-volume streets—which often lack designated infrastructure but have lower vehicle traffic—may be more conducive to cycling than major streets with designated cycling infrastructure. Cycling may also be less convenient in areas with the highest street density, which tend to have large pedestrian volumes and ample access to other travel modes. Furthermore, this finding may be attributable to our methods for simulating the most likely commute route, as participants did not report their actual route as part of the travel survey. The different associations for measures of connectivity along the commute route (negative) and at the home and work locations (positive) could relate to differences between the actual and simulated commute routes, or to differences in perceptions of connectivity as a barrier along objectively “optimal” travel routes.

The presence of public bicycle parking racks near work was also inversely associated with cycling, suggesting that bicycle commute trips were less likely when they ended in areas with more trip-end facilities. This unexpected finding may reflect the greater availability of public bicycle parking in areas that are conducive to pedestrian travel. The presence of bicycle parking was strongly correlated with the intensity of commercial development ( $\rho = 0.78$ ; results not shown), suggesting that these facilities are abundant in areas that are likely to have high pedestrian volumes, where cycling tends to be a slower and less attractive travel alternative. A similar explanation may be offered for the negative coefficient for land use mix near work, as areas with diverse land uses may also attract substantial pedestrian traffic.

The other two measures of land use considered in this study—population density and commercial intensity—were not associated with bicycle commuting in any of the regression models. These findings accord with past studies that have found land use to be a weak predictor of travel behavior after accounting for sociodemographic characteristics and environmental perceptions (Cervero and Duncan, 2003; Kitamura et al., 1997; Hoehner et al., 2005). The results may also be attributable to fairly uniform density and commercial intensity throughout our urban study area.

## 5.3. Further exploration of self-reported and objective measures

Perceived and objective environmental measures may have varying impacts on travel behavior and thus different implications for planning and policy intervention (Dill and Voros, 2007; Hoehner et al., 2005). To explore this possibility, we examined the correlation between self-reported and objective measures of the cycling environment and compared indicators of statistical fit across the four regression models.

Study participants gave self-reported information on three cycling infrastructure characteristics that were also measured objectively: *Bicing* stations near home and work, and presence of bicycle lanes or paths along at least two-thirds of the commute route. While the self-reported and objective variables did not measure precisely the same constructs (e.g., proximity to a *Bicing* station versus count of *Bicing* stations, bicycle lanes along the actual versus the simulated commute route), each pair of variables was positively correlated. These associations, however, were relatively modest ( $\rho = 0.25$  for *Bicing* at home,  $\rho = 0.24$  for *Bicing* at work, and  $\rho = 0.43$  for bicycle lanes along route; similar correlations among cyclists and non-cyclists with the exception of *Bicing* at home ( $\rho = 0.14$  among cyclists,  $\rho = 0.31$  among non-cyclists)). Thus, while self-reported and objective measures of the same environmental features tended to move in the same direction, these measures were distinct.

Next, we compared measures of fit across the four regression models. As expected, statistical fit was lowest (McFadden's adjusted  $R^2 = 0.18$ ) for the baseline model (Model 0). The improvement in fit was greater when self-reported environmental measures were introduced (Model A, 0.22) than when objective environmental measures were added (Model B, 0.20). While fit was greatest in the combined Model C (0.23), this increase was a very modest improvement upon the model with self-reported environmental measures alone (Model A).

A similar pattern was evident in the alternative-specific constants (ASCs) for cycling. The cycling ASCs for the baseline and objective models (Models 0 and B) were relatively large and statistically significant, while those for the self-reported and combined models (Models A and C) were smaller and non-significant. The high ASC values for Models 0 and B suggest that these specifications omitted relevant variables, the effects of which were absorbed into the cycling constant. The ASCs were not statistically significant in the models incorporating self-reported measures (Models A and C), further illustrating the significant contribution of self-reported environmental characteristics to the mode choice model.

These results, combined with the non-significance of key objective variables once self-reported measures were accounted for, suggest that both self-reported and objectively measured environmental characteristics are relevant to cycling mode choice but that perceptions may be stronger predictors. This attests to the importance of including self-reported measures in mode choice model specifications. These results correspond with past research that has found perceptions of the built environment to be significant predictors of cycling mode choice, independent of objective measures of the same environmental features (Dill and Voros, 2007; Hoehner et al., 2005; McGinn et al., 2007).

More broadly, the results suggest that interventions designed to promote cycling may be more successful if they target not only cycling infrastructure itself, but also *perceptions* of that infrastructure among current and potential cyclists. This result is encouraging from the perspective of fiscal resources, as awareness campaigns and educational materials are often low-cost strategies—particularly in comparison to infrastructure investments—that are nevertheless likely to have a meaningful impact on cycling, given adequate infrastructure supports.

#### 5.4. Transportation policies and programs

Respondents whose schools or employers offered incentives not to commute by private vehicle were less likely to cycle to work. This may reflect the frequent emphasis of workplace-based travel demand management (TDM) strategies on public transport, often through the provision of public transport passes for free or at reduced rates. Among the 37 respondents in our sample who reported access to this type of incentive, none used the automobile as their primary commute mode (i.e. mode consuming the greatest proportion of travel time) and approximately half ( $n = 19$ ) traveled primarily by public transport (data not shown). The travel survey did not collect information about the specific type of travel demand incentive offered, but these figures suggest that TDM incentives—which may reduce private vehicle use—were largely focused on public transport in this sample. Past research has similarly found the availability of free, employer-provided public transport passes to have a negative impact on cycling (Heinen et al., 2010).

Modal competition between cycling and public transport was also evident in the results for public transport stop counts, which were consistently and inversely associated with bicycle commuting when measured at the home location. This implies that individuals who lived in areas well served by the public transport system were less likely to commute by bicycle. Public transport availability at the work location was not associated with bicycle commuting, perhaps because the density of public transport stops is more uniformly high in employment centers than in residential neighborhoods.

Taken together, these results suggest that public transport and cycling modes may be more competitive than complementary for this sample in the municipality of Barcelona. Although public transport use may contribute to additional walking (Morency et al., 2011), commuting by bicycle is likely to generate greater gains in physical activity. Thus, a stronger focus on cycling—and on integrating public transport and cycling modes—could expand modal choice and lead to corresponding improvements in physical activity and health.

The resulting policy implications are twofold. First, TDM programs should be designed to explicitly encourage cycling in addition to public transport. This could occur through the provision of *Bicing* passes or direct financial incentives, an approach that may be particularly effective given that past research has found cycling to be more responsive to financial incentives than to widespread availability of cycling infrastructure (Wardman et al., 2007). Second, efforts should be made to promote public transport and cycling as complementary rather than competing modes. While integration of these modes already occurs through the siting of *Bicing* stations near major public transport stops and through policies that allow bicycles on public transport vehicles during certain times of the day, education campaigns could serve to increase awareness and uptake of these options among commuters. Additionally, these strategies could be complemented by more tangible financial incentives for combined public transport and cycling trips, such as reduced public transport fares when used in conjunction

with *Bicing* or a single fare card for both systems. This type of multifaceted approach is critical because past research has indicated that a comprehensive, coordinated package of cycling interventions is likely to have a greater impact than any single strategy in isolation (Pucher et al., 2010b; Noland and Kunreuther, 1995).

### 5.5. Relative importance of planning- and policy-relevant variables

To explore the relative magnitude of planning- and policy-relevant predictors of cycling, we estimated probability-weighted average point elasticities (continuous variables) and percent change values (categorical variables) for selected independent variables. These calculations are useful because the regression coefficients in Table 4 cannot be directly compared due to scale differences both across measures and across the four mode choice models. We focused on independent variables that are amenable to change by planners and policy makers and that were significant in at least one regression model. Given the interest in both self-reported and objective measures for this comparison, we calculated these values from the final combined regression model (Model C).

The probability-weighted average point elasticities for cycling are presented in Table 5. As described in Section 3.4, elasticities were calculated for individual respondents and then averaged across the sample; in the average calculation, individual elasticities were weighted by respondents' initial predicted probability of cycling in Model C, in order to give more weight to individuals with a higher baseline probability of selecting cycling as a travel mode. The resulting values represent the percent change in the probability of commuting by bicycle given a one-percent increase in the variable of interest.

Based on these findings, the probability of commuting by bicycle is most strongly associated with public transport stop presence, route-level bicycle network connectivity, and bicycle parking; these three relationships, as previously described, are in the negative direction. Bicycle network connectivity at home and at work appear to have comparable positive associations, while cycling is more strongly associated with *Bicing* presence near work than near home. The elasticity for objectively measured bicycle lanes near work is smaller by comparison, suggesting that policy and planning measures focused on modal integration and connectivity may generate greater gains in cycling mode share. All five calculated elasticities are substantially less than 1 and greater than  $-1$ , suggesting that the demand for cycling is inelastic with respect to the attributes of interest. All calculated elasticities, however, are statistically significant.

The probability-weighted average percent change values for categorical variables are presented in Table 6. These values represent the percent change in the predicted probability of commuting by bicycle when response categories are shifted for the variable of interest. As with the point elasticities and as described in Section 3.4, percent change values were calculated for each individual respondent and a weighted average (weighted by the initial predicted probability of cycling in Model C) was calculated across the sample. The greatest average responses were for the incentive variable, estimating that provision of a travel demand incentive would be associated with an 11.3% decrease in the probability of commuting by bicycle and that removal of this incentive would lead to a 10.6% increase in the probability of cycling. The average percent change values are slightly smaller for the bicycle lanes variable, and even smaller for self-reported access to *Bicing* stations at home. The mean percent change values for all three categorical variables are statistically significant.

Taken together, these findings suggest that bicycle commuting in urban areas may be most responsive to public transport stop presence and shifts in the availability of travel demand incentives, which typically promote public transport use. Estimated associations with cycling infrastructure were somewhat smaller in magnitude, particularly when measured objectively. Although these values represent simulated responses to artificial changes in the attributes of interest, the results further illustrate that diverse, complementary interventions beyond infrastructure provision—with a particular emphasis on modal integration—may generate the greatest gains in cycling mode share.

### 5.6. Sensitivity analysis: Exclusion of non-*Bicing* cyclists

Of the 361 cyclists in our study sample, the majority (76.2%,  $n = 275$ ) commuted by *Bicing*. The predictors of bicycle commuting may differ for *Bicing* and non-*Bicing* cyclists, particularly given that several of the environmental variables in this

**Table 5**  
Probability-weighted average point elasticities of cycling for selected variables from Model C<sup>a</sup>.

| Variable                      | Estimated point elasticity |        |                 |           | p-Value (for mean) |
|-------------------------------|----------------------------|--------|-----------------|-----------|--------------------|
|                               | 25th percentile            | Mean   | 75th percentile | Std. Dev. |                    |
| <i>Bicing</i> stations – home | 0.012                      | 0.034  | 0.047           | 0.027     | 0.000***           |
| <i>Bicing</i> stations – work | 0.022                      | 0.077  | 0.113           | 0.064     | 0.000***           |
| Bicycle lanes – work          | 0.009                      | 0.039  | 0.061           | 0.037     | 0.000***           |
| Bicycle connectivity – home   | 0.041                      | 0.088  | 0.131           | 0.066     | 0.000***           |
| Bicycle connectivity – route  | –0.193                     | –0.143 | –0.074          | 0.096     | 0.000***           |
| Bicycle connectivity – work   | 0.033                      | 0.087  | 0.122           | 0.076     | 0.000***           |
| Bicycle parking – work        | –0.214                     | –0.141 | –0.037          | 0.118     | 0.000***           |
| Public transport stops – home | –0.189                     | –0.136 | –0.077          | 0.078     | 0.000***           |
| Land use mix – work           | 0.023                      | 0.064  | 0.100           | 0.050     | 0.000***           |

<sup>a</sup> All values compiled across ten imputed data sets using Rubin's combination rules (Rubin, 1987).

\*\*\* Significant at 99% confidence.

mode choice analysis were related to *Bicing* station availability. Indeed, other work with the TAPAS travel survey has suggested that *Bicing* and non-*Bicing* cyclists perceive different sets of cycling motivators and barriers (Curto et al., 2016).

To assess these potential differences, we conducted a sensitivity analysis in which the regression models were re-estimated excluding the 86 non-*Bicing* cyclists (i.e. cyclists who used their own bicycle). The results were generally similar to those recorded using the full study sample, with several exceptions (results not shown). First, the negative coefficients for travel demand incentives were much stronger and statistically significant across all four regression models, suggesting that *Bicing* users may be particularly sensitive to competing incentives that emphasize public transport use. Second, the coefficients for self-reported presence of *Bicing* stations near home were smaller and not consistently significant across regression models. This finding is somewhat surprising, given the expectation that the availability of *Bicing* stations would be more important for *Bicing* users. It could be, however, that the presence of *Bicing* stations creates an environment that is perceived as conducive to all forms of cycling, bolstering the argument that bicycle sharing programs may increase the use of personal bicycles as well.

Third, the coefficients for objectively measured *Bicing* stations, bicycle lanes, and bicycle network connectivity became somewhat stronger at the work location, indicating that *Bicing* users may place greater value on cycling infrastructure in the work or school environment. Finally, the coefficients for commercial intensity reached statistical significance when non-*Bicing* cyclists were excluded, showing an inverse association at the home location and a positive association at the work location. These differences in coefficient direction may reflect competing qualities of areas with higher levels of commercial development: they are likely to offer a greater number of destinations, but they may be well served by other modes of transportation and could have high volumes of pedestrian traffic that make cycling difficult. The results of this sensitivity analysis suggest that, among *Bicing* users in particular, the former effect (i.e. greater number of destinations) may operate within the work environment to encourage bicycle commuting, but the latter (i.e. competing modes) may operate within the residential environment as a deterrent to bicycle commuting.

### 5.7. Study strengths

This study used data from a survey designed specifically for the purpose of analyzing bicycle commuting in the municipality of Barcelona. This design allowed for the consideration of multiple planning- and policy-relevant correlates of cycling mode choice, including infrastructure characteristics, the city's bicycle sharing program, and employer-based travel demand incentives. Although the commute to work or school constitutes just one of many trip purposes, this trip may be particularly important from the perspective of health promotion and congestion management because it is a daily activity that tends to be temporally constrained. Similarly, although we focused on trips that both began and ended within the municipality of Barcelona, this trip pattern accounts for 71% of all trips that are either within Barcelona or between Barcelona and the surrounding metropolitan area (Ajuntament de Barcelona, 2012). Thus, the municipality is an important geographic area for analyzing travel behavior in Barcelona.

The self-reported and objective measures in this study were considered at multiple spatial scales—including home, work, and travel route—to account for the potentially distinct influences of these three zones. Additionally, while many studies have grouped walking and cycling into a single measure of active transportation, this study assessed cycling on its own in order to more fully reflect and understand the unique characteristics of this travel mode.

### 5.8. Study limitations

Due to the cross-sectional nature of this study, the results do not address behavioral responses to policy interventions and can therefore be interpreted only as associations, rather than causal relationships. Multiple directions of causality are pos-

**Table 6**

Probability-weighted average percent change in propensity to cycle given changes in selected categorical variables from Model C<sup>a</sup>.

| Variable and change(s) in level          | Estimated percent change |        |                 |           | p-Value (for mean) |
|--|--------------------------|--------|-----------------|-----------|--------------------|
|  | 25th percentile          | Mean   | 75th percentile | Std. Dev. |                    |
| <i>Incentive</i>                         |                          |        |                 |           |                    |
| No to yes                                | −16.51                   | −11.32 | −6.70           | 5.55      | 0.000***           |
| Yes to no                                | 6.27                     | 10.64  | 16.18           | 5.57      | 0.000***           |
| <i>Bicycle lanes on 2/3 of route</i>     |                          |        |                 |           |                    |
| No to yes                                | 5.02                     | 9.58   | 14.47           | 5.06      | 0.000***           |
| Yes to no                                | −14.75                   | −10.56 | −6.82           | 4.52      | 0.000***           |
| <i>Bicing stations near home</i>         |                          |        |                 |           |                    |
| One-level increase in scale <sup>b</sup> | 3.65                     | 7.03   | 10.52           | 6.47      | 0.000***           |

<sup>a</sup> Reported statistics represent median values across ten imputed data sets.

<sup>b</sup> Respondents in the highest category (level = 4) were excluded from this calculation because a one-level increase could not be estimated for a new level of 5.

\*\*\* Significant at 99% confidence.



sible, as it is unclear whether self-reported information on bicycle lanes and *Bicing* availability are the cause or the consequence of travel behavior. Additionally, the results for cycling infrastructure may be biased by residential or employment self-selection, as individuals who prefer to commute by bicycle may choose to live or work in close proximity to cycling infrastructure, while those who do not have this preference may live farther from cycling infrastructure. However, the higher likelihood of bicycle commuting among residents and employees in cycling-supportive environments could suggest that cycling infrastructure will be used if it is provided (Dill and Carr, 2003).

Multiple imputation methods were required due to non-response on several survey questions, particularly household income. This process may have introduced uncertainty into the regression models. To assess this possibility, we performed all of our statistical analyses on the subset of participants with complete data on all regression variables ( $n = 454$ ). This process yielded a similar pattern of results (e.g., coefficient direction, statistical significance; results not shown) and did not change the major conclusions of the analysis, lending confidence to the results from our imputed data set.

The travel survey asked only for information on respondents' morning commute from home to work or school. It is possible that different associations would be observed for the evening commute, but these potential differences could not be evaluated due to the survey design. This limitation may be particularly relevant to the relationship between slope and *Bicing* use: due to the topography of the city, many Barcelona commuters use *Bicing* for their inbound (downhill) trip to work but use public transport for their return (uphill) trip.

The results may also have been affected by measurement error, particularly for the objective environmental variables. As participants did not describe their actual commute route, we were required to simulate the route most likely taken based on distance and infrastructure characteristics. This may have introduced error, and the inverse associations of route-level infrastructure variables with cycling should be interpreted with caution. More broadly, potential measurement error in the GIS-based variables may have attenuated the coefficients and elasticities observed in this analysis.

Finally, the relatively low mode share of cycling in Barcelona necessitated a sampling design that over-represented cyclists, who were preferentially approached by interviewers during the recruitment effort. This strategy was important because it provided adequate statistical power for examining cycling in Barcelona, but it may have introduced selection bias. Similar bias could result from the relatively low response rate in terms of completed travel surveys. Although the results should therefore not be interpreted as representative of general commuting behavior in Barcelona, they are still illustrative of the underlying mode choice relationships of interest.

## 6. Conclusions

This study assessed the potential for short- to medium-term planning and policy interventions to promote cycling in a large European urban area. The results provide insight into variables that explain—and could thus encourage—cycling among urban commuters.

Based on this analysis, both self-reported and objective measures of cycling infrastructure are associated with bicycle commuting. However, regression models that incorporate self-reported measures of cycling-supportive infrastructure may provide a more thorough understanding of mode choice than those that rely solely on objective measures of these attributes. From the perspective of planning and policy intervention, this finding suggests that education campaigns designed to promote awareness of cycling infrastructure may be important complements to infrastructure investments. Given the relatively low costs associated with this type of strategy, interventions that target awareness and perceptions may be particularly viable as short-term solutions to promote cycling, and as methods to increase the feasibility and success of larger infrastructure projects.

The availability of *Bicing* stations was consistently and positively associated with bicycle commuting, offering support for continued investment in this type of program. This finding builds upon other recent work in the TAPAS study, which has suggested that bike share can serve as a “gateway” for commuters who are willing to cycle but do not already do so on a regular basis (Curto et al., 2016). Interestingly, self-reported *Bicing* availability had stronger associations with bicycle commuting when reported for the home environment, while objective measures of *Bicing* availability were stronger in the work environment. These nuances could further support education and awareness campaigns as valuable complements to infrastructure investments.

Several of the findings in this study—including the negative coefficients for bicycle parking, land use mix, and route-level bicycle connectivity—suggest that bicycle commuting may be deterred in areas with intense destination activity. This may reflect competition with other travel modes and the difficulty of cycling among high pedestrian volumes. These findings suggest that interventions to streamline cycling in this type of environment—such as increased enforcement of pedestrian crossings—may be valuable to promote cycling in urban centers.

The availability of employer-based travel demand incentives was inversely associated with bicycle commuting in all four regression models. This is likely due to the frequent focus of TDM strategies on public transport use. Modal competition between cycling and public transport was further evident in the negative coefficients for public transport stop presence. Based on these results, TDM policies should be designed to promote cycling in addition to public transport, and local transportation policies should encourage the integration of these two complementary modes of travel.

Finally, although the primary focus of this study was on the potential for short- to medium-term actions to encourage cycling, land use characteristics were also considered to assess the importance of longer-term planning strategies. The pri-

**Table A1**

Comparison of study sample and Barcelona residents for selected sociodemographic characteristics.

| Characteristic                      | Study sample (n = 765) | Barcelona city |
|-------------------------------------|------------------------|----------------|
| Percent female                      | 51.9                   | 52.5           |
| Average age (years)                 | 36.4                   | 43.5           |
| Average monthly income (€)          | 2000–3000              | 2700           |
| Percent of households with children | 35.6                   | 21             |

marily non-significant coefficients for these variables could indicate that land use attributes are not strongly associated with bicycle commuting in the municipality of Barcelona, contributing to an evolving yet somewhat inconclusive literature surrounding the built environment and travel behavior. The findings generally suggest, however, that cycling infrastructure—including the density and connectivity of the bicycle lane network—may offer the most promising starting point for built environment interventions intended to encourage cycling in urban centers.

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## Appendix A.

See [Table A1](#).

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