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Going a long way? On your bike! Comparing the distances for which public bicycle sharing system and private bicycles are used

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A B S T R A C T

Cities are implementing an ever widening range of initiatives to promote bicycle use with the aim of improving the sustainability of urban journeys. One strategy that is achieving the most immediate results in the promotion of bicycle use, along with the construction of bicycle lanes and bicycle parking, is the implementation of Public Bicycle Sharing Systems (PBSS), which coexist with private bicycle use. As both these systems (PBSS and the private bicycles) have their advantages and disadvantages, this paper seeks to compare the distances for which PBSS and private bicycles are habitually used by applying a propensity score matching-based model. Our findings unequivocally demonstrate that the mean journey length made by private bicycle is 700–800 m (0.44–0.5 miles) greater than those made by public bicycle. We find robust empirical evidence that there is a complementarity relationship between the two modes of transport with regard to distance. The conclusions of this study are useful for the PBSS literature in spatial/geographical terms, for the management of PBSS hire charges, and in relation to the system's suitability for different city models.

1. Introduction

Many large cities worldwide have implemented Public Bicycle Sharing Systems (hereinafter PBSS) due to their potential to motivate bicycle use (Fishman, Washington, & Haworth, 2012, 2013) and their recognition as one of the most sustainable and economical modes of transport, providing many benefits in terms of health, urban traffic and the environment (Handy, Van Wee, & Kroesen, 2014; Pucher & Buehler, 2012).

The recent academic literature has examined PBSS in greater depth from a number of different perspectives and has identified the various aspects that affect the frequency of their use (Bachand-Marleau, Lee, & El-Geneidy, 2012), and the advantages and disadvantages that they offer. Among the advantages are the fact that they are flexible systems that are convenient for city-dwellers (Shaheen, Guzman, & Zhang, 2010); that the bicycle can be used in combination with public transport (Jäppinen, Toivonen, & Salonen, 2013), and that issues such as theft and lack of parking space are minimized (Fishman et al., 2012). Among the disadvantages that can be highlighted are the vandalism that they are subjected to (Castillo-Manzano & Sánchez-Braza, 2013b), the inadequate distribution of bicycles at docking stations and choice of sites for their location (Erdoğan, Laporte, & Wolfler Calvo, 2014; García-Palomares, Gutiérrez, & Latorre, 2012), and the imbalance between bicycle supply and demand (Castillo-Manzano & Sánchez-Braza, 2013a). Other researchers such as Lin and Yang (2011) have also analyzed certain limitations to PBSS systems with respect to urban planning (especially in city center districts), as sufficient space is needed to install the number of stations required to cover the demand for bicycles (see also Lin, Yang, & Chang, 2013).

However, following Fishman et al. (2013), studies that evaluate PBSS from the spatial point of view are scarce, including evaluations of the distance covered by users, for example, despite the fact that distance is a key factor that affects the choice to use the bicycle (Heinen, Maat, & Wee, 2011a). Journey distance is therefore pivotal when deciding whether to use the bicycle or not, and so might also act as a major barrier (Handy et al., 2014; Rybarczyk & Gallagher, 2014), with greater distances to work, school or other destinations resulting in fewer and less frequent journeys habitually made by bicycle (Gatersleben & Appleton, 2007; Handy & Xing, 2011; Zhao, 2014). Distance could also play a very different role in daily decisions to make bicycle journeys depending on the type of cyclist

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(Heinen, Maat, & Van Wee, 2011b) or the purpose of the journey (Iacono, Krizek, & El-Geneidy, 2008).

Along with distance, other studies have pointed to the decision to use the bicycle possibly being influenced by a variety of other factors that might act as facilitators or barriers. In the first group are demographic and personal characteristics, such as age (Ma, Liu, & Erdogan, 2015); cultural tradition (Rietveld & Daniel, 2004); car ownership (Wuerzer & Mason, 2015); individual activities, such as picking up/dropping off children or carrying the shopping (Mullan, 2012); bicycle users' personal preferences (Heinen et al., 2011a); or other social/psychological variables, such as the way cyclists are perceived socially in a world dominated by car transport (Nankervis, 1999). The second group includes aspects related to the terrain and design of the city, such as its size (Martens, 2004); the type of city and urban layout (Hansen & Nielsen, 2014; Ma et al., 2015); the pedestrian environment (Timperio et al., 2006); elevation of the work/study address (Cole-Hunter et al., 2015); greater residential density (Heinen, Van Wee, & Maat, 2010; Pucher & Buehler, 2006); level of urban greenness around the work/study address (Cole-Hunter et al., 2015); or mixed-use development (Pucher & Buehler, 2006); and even the city or country's socio-economic features, such as the level of income or the costs involved in owning, driving and parking a car (Pucher & Buehler, 2006). In addition, environmental factors also play a core role, including temperature, light conditions, precipitation and wind (Spencer, Watts, Vivanco, & Flynn, 2013) and even human thermal perception (Bradenburg, Matzarakis, & Arnberger., 2004), with a distinction made between weather conditions and the climate and seasonal variation patterns (Nankervis, 1999). Finally, in a third group Pucher, Dill, and Handy (2010) highlight the crucial role of public policy in encouraging cycling, which requires many different and complementary interventions, including the bicycle infrastructure environment (Snizek, SickNielsen, & Skov-Petersen, 2013) and the spread of public bike sharing systems (Parkes, Marsden, Shaheen, & Cohen, 2013); safer cycling conditions, benefited by stricter police enforcement of traffic regulations and restrictions on car use (Pucher et al. 2010); and cycling training and traffic education programs (Pucher & Buehler, 2006). Firms and campuses can also overcome barriers to bicycle use by providing bike storage and showering and changing facilities (Ransdell, Mason, Wuerzer, & Leung, 2013).

Numerous other studies have sought to quantify the distance covered using the bicycle as a means of transport. For example, Keijer and Rietveld (2000), Rietveld (2000)find that bicycles are used more frequently for distances of 0.5–3.5 kms (0.31–2.17 miles), while Ma et al. (2015), van Wee, Rietveld, and Meurs (2006), Buehler (2012), Li, Wang, Yang, and Jiang (2013) and Millward, Spinney, and Scott (2013) state that bicycles seem to be used more frequently for medium distance journeys (2–5 km (1.24–3.1 miles)). Yang, Li, Wang, Zhao, and Chen (2013) consider that bicycle travel distance is less than 6 km (3.72 miles) and expected travel duration is 30 min or less. Greater distances are found in Akar and Clifton (2009), who consider a distance of 8 km (4.96 miles) as a limit for bicycle use; whereas Heinen et al. (2011a) state that most cycling journeys are less than 15 km (9.3 miles). Yet further studies analyze the distance to public transport connections, highlighting the role that the bicycle plays as an interconnector (Yang et al., 2013). In this respect, Martens (2004) explains that most bicycle users are willing to cycle 2–5 km (1.24–3.1 miles) to a public transport stop depending on the speed of the public transport in question. The bicycle therefore has an advantage for interconnections over short distances compared to its competitors, such as walking, for example (Keijer & Rietveld, 2000), with 2.5 km (1.55 miles) being the threshold when people switch from walking to cycling (Zacharias, 2005).

Focusing on PBSS, some studies quantify the distance covered by their users. The following can be cited: Jensen, Rouquier, Ovtracht, and Robardet (2010), who consider a mean journey distance of 2.49 km (1.5 miles) and a mean journey duration of just under 15 min for the Lyon PBSS; Ma et al. (2015), who find that the majority of journeys by public bicycle in Washington, D.C. are about 1.6 km (1 mile) in length; and Zhang, Xu, and Yang (2015), who establish that PBSS are designed for short journeys of 0.8–4.8 kms (0.5–3 miles).

However, prior studies that analyze the relationship between journey length and bicycle use do not detail the difference in the distance covered by PBSS users and private bicycle owners. Even when analyzing the important role of the bicycle in general as a commuter mode of transportation (Nkurunziza, Zuidgeest, Brussel, & Van Maarseveen, 2012) the academic literature highlights the greater prevalence of shorter distances (Heinen et al. 2010), but does not differentiate between the private bicycle and the PBSS. The latter has now also become an appropriate mode for the daily journey to work or school (Martin & Shaheen, 2014; Shaheen, Zhang, Martin, & Guzman, 2011, 2012), but short commutes are once again more prevalent (Karki & Tao, 2016; Shaheen et al., 2012) with the bicycle giving way to other modes of transport for longer commute distances (Martin & Shaheen, 2014).

Given the lack of literature comparing the two types of bicycle, the objective of this study is to establish the difference in the distance habitually covered using each. Taking as our case study the city of Seville (Spain), we believe that our research could shed light on this issue since, as Mullan (2012) states, more research needs to be conducted into distances for which bicycles are used, and this is perhaps especially interesting in the case of PBSS (Fishman et al., 2013).

In short, the purpose of our study is to assess the degree to which the implementation of a PBSS in Seville has influenced cyclists' decisions to opt for using one type of bicycle or the other depending on the number of meters to be covered. Applying a propensity score matching-based model to a database constructed from a survey of PBSS and private bicycle users in the city of Seville, our study makes an entirely original contribution by indicating a suitable level of public service contingent on journey distance.

A number of different focuses can be used to analyze the effect of any given transport policy action such as that analyzed in this paper, ranging from a simple descriptive analysis to more analytical approaches. In our case, the proposed methodology is framed within the area of statistical causal inference, which is based on the estimation of the causal effect that a specific measure or action has on one or more relevant variables (Pearl, 2000). We therefore follow the so-called "Rubin causal model" (Rubin, 1974) as it was initially developed, with the subsequent contributions made by Holland (1986) taken as the starting point for the use of this model. Compared to traditional or simply descriptive analyses, this methodology enables consistent estimators of an action's effects to be obtained and isolates the effects of any contaminating variables (Rotnitzky & Robins, 1995).

Based on processes that originated out of medical experimentation, causal inference techniques are currently widely used in multiple scientific disciplines, ranging from medicine itself (Christakis & Iwashyna, 2003; Hirano & Imbens, 2001;) to a number of areas in the field of the Social Sciences, such as sociology (Morgan & Harding, 2006); the political sciences (Duch & Stevenson, 2006; Imai, 2005); and the economic evaluation of public policies (Cansino, Lopez-Melendo, Pablo-Romero, & Sánchez-Braza, 2013), to cite but a few examples. In recent years the application of this methodology has spread further in the economic evaluation scenario to include the evaluation of actions and behaviors related to transportation policies.

Some examples of studies that analyze the effect of adopting certain specific transportation policies can be cited: Aul and Davis (2006) estimate crash modification factors associated with signalizing a set of nonrural intersections; Karlström and Franklin (2009) address the effects of a congestion pricing system in terms of both travel behavioral adjustments and welfare effects; Castillo-Manzano and Sánchez-Braza (2011) explore the establishment of a flat rate for the taxicab service and the impact of this flat rate on the likelihood of passengers choosing a taxicab for their city–airport transport needs; Wood and Porter (2013) assess the safety impacts of design exceptions on roads; Cao and Schoner (2014) evaluate the impact of a light rail transit system on transit use; Canavan et al. (2015) analyze the effect of introducing moving-block signaling on the technical efficiency of urban metro rail systems; and Whitehead, Franklin, and Washington (2015) evaluate the effects on distances traveled and greenhouse gas emission levels of the adoption of two transport policies, the establishment of a congestion-pricing scheme and the approval of measures to encourage vehicle owners to transition to energy efficient vehicles.

Other studies should also be mentioned that apply this methodology to the analysis of user behavior for the different modes of transport. For example, Castillo-Manzano (2010) examines the difference in behavior of low-cost and network airline passengers when determining their transport mode for travel to airports; Funderburg, Nixon, Boarnet, and Ferguson (2010) examine the association between new highway investments and land use change; Cao (2010) analyzes whether alterations to the built environment are a cost-effective way to change travel behavior by exploring the causal effect of neighborhood type on walking behavior; Cao, Xu, and Fan (2010) explore the influence of residential locations on driving, evaluating the way that the built environment impacts travel behavior. Parady, Takami, and Harata (2014) also study the connection between the built environment and travel behavior, suggesting the existence of a causal mode substitution mechanism from car to nonmotorized modes given positive increases in the latent score of urbanization level; and Oliveira, Moura, Viana, Tigre, and Sampaio (2015) analyze the relationship between commuting time and health outcomes.

For the objective of our study we perform a two stage evaluation procedure following specifications in studies such as Heckman and Vytlacil (2005), Abadie and Imbens (2006), and Hahn, Hirano, and Karlan (2011). The first step is to estimate the propensity score, as defined by Rosenbaum and Rubin (1983). Next, the matching estimators are found using radius, kernel and stratification matching methods, in accordance with proposals in studies by Becker and Ichino (2002), Dehejia and Wahba (2002), Imbens (2004), and Cameron and Trivedi (2005).

The paper is structured as follows. The second section presents the data used in the models. The third section contains a brief explanation of the methodological model and data processing. The fourth and fifth sections are devoted to the results and the discussion of these findings, respectively. Finally, Section 6 presents the conclusions of the study.

2. Data

The data in the present study are taken from a survey of PBSS (SEVici) and private bicycle users in the city of Seville (Castillo-Manzano, Lopez-Valpuesta & Marchena-Gómez, 2015). Table 1 shows the main features of this survey.

As stated below in the methodology section, to carry out the proposed evaluation process a series of variables has to be constructed from the data obtained in the survey. We first define the binary variable D as a participation indicator of the measure to be evaluated. This variable D captures whether individuals have opted for the PBSS as an urban transport mode ($D_i = 1$), or whether they have made their journeys using their own bicycles ($D_i = 0$). The sample observations are thus divided into a participant and a control group. We also define the Y variable as the variable on which the causal effect of the measure being analyzed will be evaluated. In this case, variable Y is defined as the length, i.e., the distance in meters, of journeys made by bicycle (public or private). Table 2 gives the definitions of these variables and their main descriptive statistics for the whole of the sample (N = 1904).

However, additional variables, or covariates, also have to be defined and controlled for to ensure that they do not contaminate the estimated results of the causal effect (see methodology appendix to explore the proposed methodology in greater depth). To be specific, the covariates vector used consists of nine variables that provide information about both the characteristics of the individuals and the journeys that they have made.

Once again, Table 2 gives the definitions of these covariates and their main descriptive statistics for the whole of the sample divided into three information blocks according to the variables chosen by the previous studies cited in the introduction: the personal characteristics of the individuals, their reasons or motives for using the bicycle to make their journeys, and the point of journey origin and destination in order to take into account the city's urban layout (in the historic city center, for example, the bicycle lane network is more restricted for obvious reasons and there are also pedestrianized areas where bicycle access is limited).

It is also interesting to present a comparison of the values of these covariates' main descriptive statistics for the two groups of individuals considered –participant and control-so that, given the possible between-group differences in value for each of the variables, it becomes clear whether these need to be controlled for when making a comparison between the two groups. Thus Table 3 gives the main descriptive statistics for these covariates for each of the groups: participant ($n_1 = 1400$) and control ($n_0 = 504$).

The characteristics of Seville make the city a perfect testing ground for our analysis, and somewhat reduces the need for additional covariates to be included. First, the terrain in Seville is very flat in all parts of the city, as it sits in the Guadalquivir river valley with a mean height above sea level of only 7 m. Obviously, in a city with varying terrain a variable would have to be included to capture any changes in terrain by journey.

Second, the high quality of the cycling infrastructure in Seville should be highlighted. This infrastructure has made the city an international benchmark for how bicycles can be successfully promoted in cities with no history of bicycle use (see Castillo-Manzano & Sánchez-Braza, 2013a; Marqués, Hernández-Herrador, & Calvo-Salazar, 2014). In fact, today Seville is the only city in the world where, in only 4 years (2006–2009), bicycle use is known to have risen from practically 0%–6.6% of mechanized journeys (see Castillo-Manzano & Sánchez-Braza, 2013b; and Marqués et al., 2014).

Third, there is an extensive 140 km + cycle lane network in a medium sized city of under 700 thousand inhabitants. With the only exception of the historic city center, this extensive network and the previously mentioned excellent terrain are constants throughout the city, irrespective of bicycle users' districts of origin and/or destination. The urban morphology of the historic city center includes some gentle slopes and the narrow streets prevent the construction of cycle lanes as in the rest of the city, whereby two specific covariates have been included to correct any bias that might occur through the inclusion of the area in the analysis, namely origin-center and destination-center (see Table 2).

Fourth, the PBSS docking stations are in close proximity to one another (see Fig. 1 and, for greater detail, http://www.sevici.es/layout/set/fullmap/Estaciones/Mapa) resulting in one of the

Table 1
Survey campaign.

Fieldwork	**Location, public bicycle users**	Random selection of SEVici stations (weighted by usage according to City Hall reports). Surveys were specifically conducted when bicycles were being returned.
	Location, private bicycle users	Assorted main city bicycle lanes (interviewers were stationed at traffic lights and in the main private bicycle parks in the city) (educational establishments, public organizations, and a variety of main transport stations).
	Period	Two waves in March and April 2014 (local holidays and rain days omitted).
	Schedule	8 am to 8 pm (despite 8 h working days) to capture a sample of different cyclist profiles by time schedule (i.e. for reasons of leisure, work or study).
Information source	**Interviews with closed questionnaire**	22 items (to be specific, 4 are respondent personal data, which also enables an ex post evaluation of the survey's veracity; 12 items from which information is obtained on the variables in Table 2, including points of origin and destination; 3 items that define the time and place where the survey was conducted; and 3 additional items on bicycle use in conjunction with other modes of transport and level of education).
	Universe	PBSS (SEVici) and private bicycle users over the age of 15
Sampling	**Sample size**	1904 cyclists (1400 public bicycle and 504 conventional private bicycle)
	Sampling technique	Random selection of SEVici and private bicycle users in the above-mentioned places following an interview one/omit two rule.

Table 2
Variables and descriptive statistics: All individuals.

All individuals				
	Explanation	Observations	Mean	Standard deviation
Indicator and response variables				
PBSS	1 if individual has opted for the PBSS to make the journey; 0 if individual has made the journey using a private bicycle.	1400	0.735	0.441
Distance	Distance in meters of the journey made by bicycle (public or private).	–	3684.228	2231.765
Covariates				
(a) Personal characteristics. Base category: female				
Gender	1 if male; 0 otherwise.	1192	0.626	0.484
Age	Age of respondent (15–74 years).	–	29.760	11.718
Bicycle user	Length of time a bicycle user (in months).	–	42.585	45.147
(b) Motives for using bicycle as mode of transport. Base category: other motives				
Work	1 if the reason is work; 0 otherwise.	445	0.234	0.423
Study	1 if the reason is study; 0 otherwise.	973	0.511	0.500
Leisure	1 if the reason is leisure; 0 otherwise.	341	0.179	0.384
Exercise	1 if the reason is exercise; 0 otherwise.	71	0.037	0.190
(c) Point of origin or destination of the bicycle journey. Base category: neither the point of origin nor the destination are in the city center				
Origin-center	1 if the point of origin of the bicycle journey is the city center; 0 otherwise.	561	0.295	0.456
Destination-center	1 if the destination of the bicycle journey is the city center; 0 otherwise.	656	0.345	0.475

Table 3
Descriptive statistics of the covariates for participant and control groups.

	Participant group			Control group		
	Observations	Mean	Standard deviation	Observations	Mean	Standard deviation
(a) Personal characteristics. Base category: female						
Gender	895	0.639	0.480	297	0.589	0.492
Age	–	29.561	11.819	–	30.313	11.427
Bicycle user	–	32.766	23.022	–	69.859	72.272
(b) Motives for using bicycle as mode of transport. Base category: other motives						
Work	342	0.244	0.430	103	0.204	0.404
Study	701	0.501	0.500	272	0.540	0.499
Leisure	236	0.169	0.375	105	0.208	0.407
Exercise	57	0.041	0.198	14	0.028	0.164
(c) Point of origin or destination of the bicycle journey. Base category: neither the point of origin nor the destination are in the city center						
Origin-center	407	0.291	0.454	154	0.306	0.461
Destination-center	469	0.335	0.472	187	0.371	0.484

densest networks in medium sized cities in Europe. Managed by the JCDecaux Company, the PBSS has 260 docking stations, 2650 smart-bikes and 5163 individual bicycle racks. To be specific, the distance between stations is approximately 300 m (see http://www.sevici.es/Como-funciona/Puntos-de-recogida-o-entrega).
This implies that the maximum distance that any individual would have to walk to collect a bicycle (or to reach his/her destination after returning a bicycle) would be 150 m, i.e., 2 min on foot, and the mean distance would be 75 m, i.e., 1 min on foot. Notwithstanding, Google Maps was used to check that surveyed private bicycle users whose points of journey origin or destination were in less densely populated areas of the city (for example, on the city's periphery, in industrial parks, in the docks area, and so on) were properly served with available PBSS docking stations. In these exceptional cases, corresponding to under 0.1% of the surveyed cyclists, the maximum distance that would need to be walked might rise from 150 to 250–300 m, i.e., a maximum of less than 4 min on foot. In short, public bicycle availability has been verified to be not only a viable,

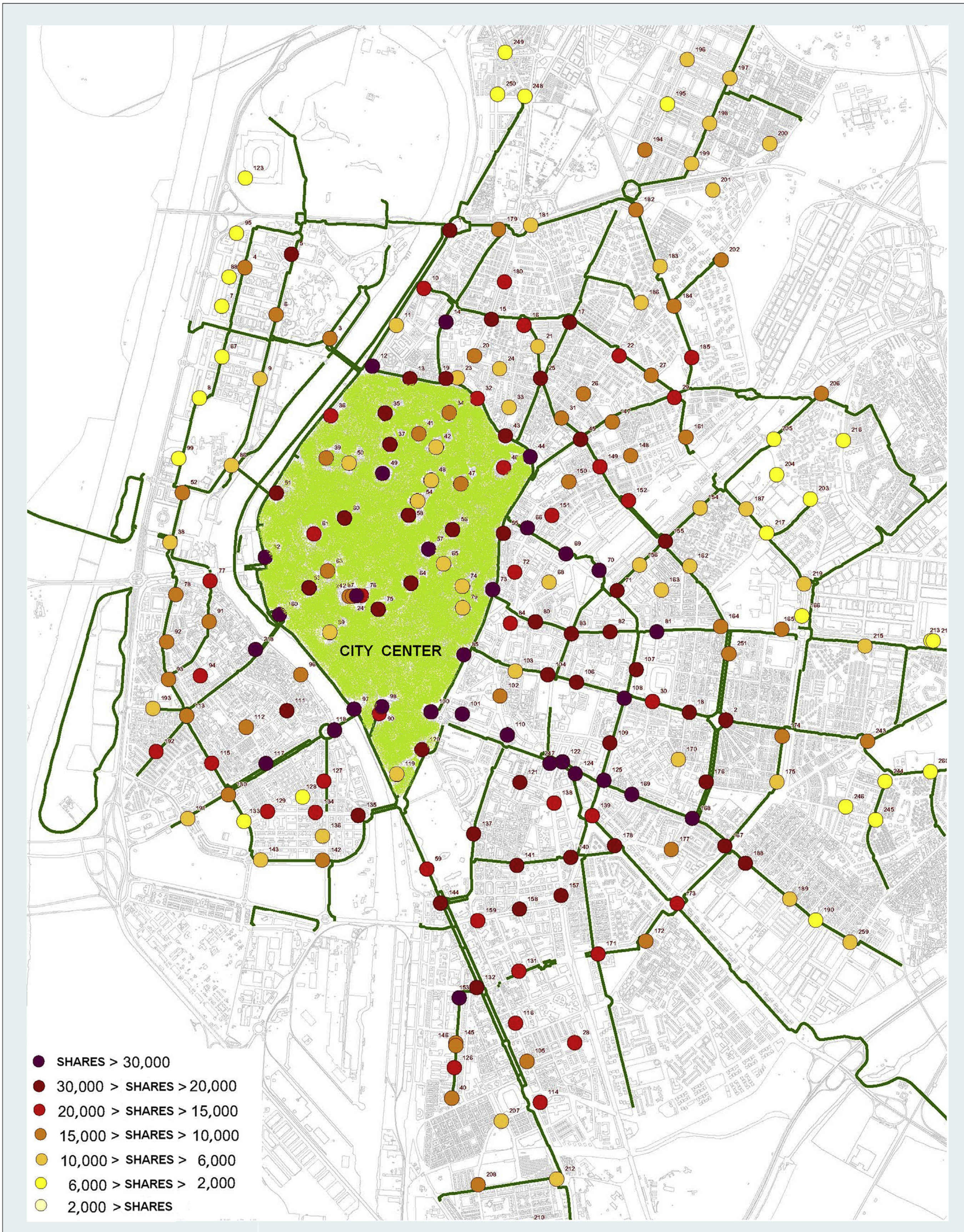

Fig. 1. Map of SEVici PBSS docking stations in Seville.

but also an efficient alternative to the private bicycle, and that no additional covariate needs to be included to capture availability.

3. Methodology

3.1. Model introduction

A concise explanation is given of the methodological approach below (a detailed version that includes all the technical details is given in the Methodological Appendix at the end of the article). The proposed methodology is framed within statistical causal inference. The measure's causal effect is captured by calculating the "Average Treatment Effect on the Treated" (ATET), which is defined as the difference between the mean response variable values for individuals who have used the PBSS and those who have used their own private bicycles, conditioned on the participant group.

A two stage procedure is followed to obtain the ATET, as other variables have to be controlled for that could impact said effect. The first step is to calculate the so-called propensity score, $\varepsilon(X)$, defined as the likelihood that a sample observation belongs to the participant group (PBSS user), conditioned on the values that a vector X of predetermined covariates adopts. The two most common models used to estimate the propensity score are the logit and probit models, opting for the model that provides the maximum log likelihood.

During the second stage, the propensity score matching technique is subsequently used to calculate the estimator of the ATET using the expression:

$$\widehat{\alpha}_{ATET} = \frac{1}{n_1} \sum_{i=1}^{n_1} \left(Y_i - Y_{m(i)} \right)$$

where $Y_{m(i)}$ is the value of the response variable Y for the control individual assigned as the pair (or the mean value, when more than one individual has been assigned) of the participating individual i. In our case, radius, kernel and stratification matching methods are used for this assignment processes. Once completed, the ATET would be obtained.

Table 4
Propensity score estimation.

Variable	Logit model	Probit model
Constant	2.982***	1.743***
	(0.485)	(0.267)
Gender	0.386***	0.226***
	(0.117)	(0.068)
Age	0.006	0.003
	(0.007)	(0.004)
Bicycle user	−0.029***	−0.017***
	(0.002)	(0.001)
Work	−0.641*	−0.345
	(0.390)	(0.216)
Study	−1.283***	−0.719***
	(0.406)	(0.223)
Leisure	−1.222***	−0.692***
	(0.401)	(0.222)
Exercise	−0.493	−0.294
	(0.514)	(0.283)
Origin-center	0.045	0.020
	(0.125)	(0.073)
Destination-center	−0.087	−0.052
	(0.120)	(0.070)
Obs.	1904	1904
Max. log. likelihood	−935.126	−937.393
Pseudo-R^2	0.151	0.148
Wald Chi^2	249.49	263.76
(p-value)	(0.000)	(0.000)

NB: Robust standard deviation corrected for heteroscedasticity is given in brackets. One, two and three asterisks indicate coefficient significance at the 10%, 5%, and 1% levels, respectively.

3.2. Data processing

Table 4 summarizes the process to estimate the propensity score. The logit model is selected as it presents the highest maximum likelihood value and propensity score values are assigned accordingly.

The resulting coefficients (see Table 4) indicate the degree to which each of the 9 covariates (see Table 2) contributes to the propensity score. The propensity score can be defined as the likelihood that the surveyed bicycle users use a PBSS bicycle in preference to a private bicycle, given the values of their covariates. The main goal is to make the individuals from the treatment and the control groups as homogeneous as possible as far as the 9 covariates are concerned. This means that the individual significance of each of the covariates is of no interest for our analysis.

All the covariates satisfy the balancing test at a 1% significance level. Individuals with similar propensity scores are therefore guaranteed to have similar covariate distributions, irrespective of the status of their participation in the measure (i.e., irrespective of whether they are in the participant or the control group).

Subsequently, propensity score values are assigned to each of the individuals. The common support condition is imposed to compare the two groups, which means that the comparison is only performed between individuals with propensity scores at the point where the two groups intersect. The distribution of the region of common support for participating and control individuals' estimated propensity scores for can be observed to verify the similarity of the compared groups (see Fig. 2).

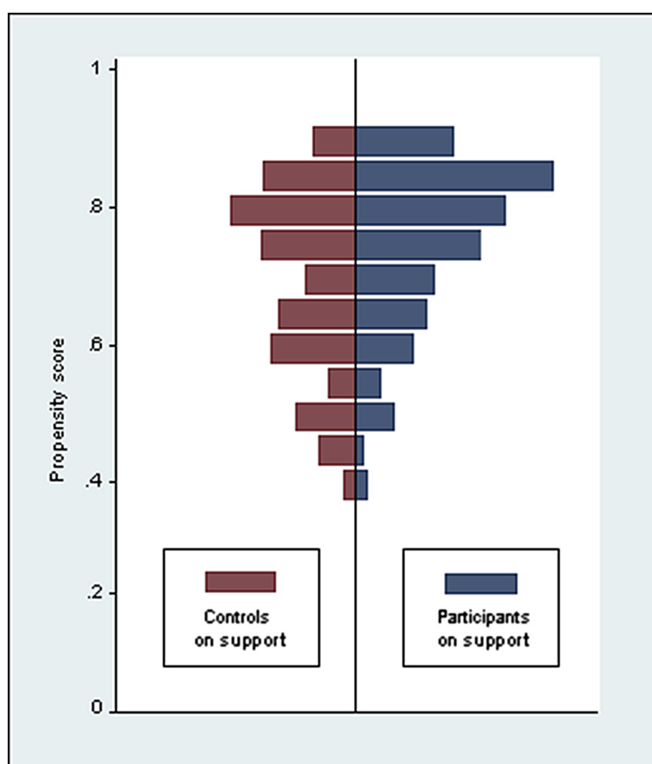

Fig. 2. Distribution of compared groups (common support region).

Table 5
Estimators of average effect of PBSS on journey distances using the radius matching method.

Radius	$\widehat{\alpha}_{ATET}$ Distance in meters	Std. Dev.	t statistic	Lik.
0.05	−805.24***	171.27	−4.70	0.000
0.10	−731.97***	164.56	−4.45	0.000
0.15	−731.53***	161.21	−4.53	0.000

*** Three asterisks indicate significance at the 1% level.

Table 6
Estimators of average effect of PBSS on journey distances using the kernel matching method.

Bandwidth	$\widehat{\alpha}_{ATET}$ Distance in meters	Std. Dev.	t statistic	Lik.
0.05	−746.19***	162.81	−4.58	0.000
0.10	−735.38***	153.15	−4.80	0.000
0.15	−724.23***	142.42	−5.09	0.000

*** Three asterisks indicate significance at the 1% level.

Table 7
Estimator of average effect of PBSS on journey distances using the stratification matching method.

No. intervals	$\widehat{\alpha}_{ATET}$ Distance in meters	Std. Dev.	t statistic	Lik.
18 intervals	−738.88***	179.10	−4.13	0.000

*** Three asterisks indicate significance at the 1% level.

4. Results

In the radius and kernel matching methods, three degrees of radius/bandwidth (0.05, 0.10 and 0.15) are used to test the obtained estimators' sensitivity to changes in the proximity level required between participant and control group individuals. In addition, both matching methods are applied with replacement. This is done with the aim of minimizing the distance between participating and assigned control individuals and helps to reduce any bias. The estimator for the stratification matching method is obtained assuming the same intervals identified by the algorithm used to estimate the propensity score. Tables 5–7 give the results.

The results show that the journey distance for PBSS bicycles is considerably lower than for private bicycles. It therefore seems clear that individuals opt for the PBSS when they have to travel short distances, whereas they opt for private bicycles when they have to travel long distances. In other words, when individuals have to make journeys of a considerable length, they eventually decide to purchase their own bicycles.

According to the results in Table 5, when radius matching is used the mean journey length using the PBSS is around 756 m less than the journey distance covered using individuals' own bicycles; between 805 and 731 less depending on the radius considered. As Table 6 shows, the results are very similar for kernel matching, with the journey distance made using the PBSS on average 735 m less than the journey distance using individuals' own bicycles; between 746 and 724 depending on the bandwidth considered. The stratification matching results in Table 7 point to the same conclusion, with the journey length for the PBSS being around 738–739 m less than the journey distance using individuals' own bicycles. All the estimators obtained are significant at 1% in all cases. The results can be seen to be consistent and very similar, whichever matching method is used and whatever the radius or bandwidth considered.

5. Discussion

The results obtained in our analysis are in line with what is found in the academic literature, which states that it is the bicycle's features and equipment (and, therefore, we could also say the PBSS' features and equipment) that influence bicycle users' decisions for the journeys that they take. For example, Handy et al. (2014), and Lovejoy and Handy (2012) state that a bicycle's characteristics and equipment level have a clear effect on how safe it is to travel by bicycle, as well as on its convenience and comfort and, therefore, on the suitability of using the bicycle for shorter or longer distances. In the same line, for authors such as Kroesen and Handy (2014), and Wardman, Tight, and Page (2007), convenience is another of the determinants for choosing the bicycle. The private bicycle offers a greater number of possibilities in this respect, as owners have more freedom to adapt the bicycle to their own needs, and are able to opt for greater comfort, greater speed and a more ergonomic model. This is consistent with the results obtained in the present study, as users seeking greater comfort for long-distance journeys would eventually opt to purchase their own bicycles rather than hire them, as private bicycles afford greater freedom, greater comfort and greater convenience.

Effort is closely connected with convenience. Specifically, journey distance is observed to correlate directly and positively with required effort (Heinen et al., 2010), which means that the disadvantages of using the bicycle are likely to rise disproportionately for longer distances (van Wee et al., 2006). For the very same reason it is to be expected that a greater distance would result in greater private bicycle use, as more physical effort is required than for the public bicycle due to the bicycle's features and equipment. In the same line, a gender difference may be assumed to exist in the physical effort that each cyclist is willing to make, with studies such as Garrard, Rose, and Lo (2008) expressing the idea that the distance that women travel to work by bicycle is usually shorter than the distance that men travel. Howard and Burns (2001) quantified the distance that men would travel as approximately 5 km (3.1 miles) more than women on average. To be specific, the mean distance for the former would be around 11.5 km (7.13 miles), whereas for the latter it would be a little over 6.5 km (4.03 miles).

On the other hand, among the motives for using the bicycle, greater distances could act as an incentive for people who use the bicycle to keep fit, do sport and for whom cycling is a leisure activity (Mullan, 2012). As it is logical to suppose that private bicycles are used for these activities, this would also be consistent with the present study in associating longer distances with the private bicycle.

Finally, PBSS tariffs should also be taken into account along with the above-mentioned characteristics; public bicycle charges could be one of the reasons for making shorter journeys, as users are sometimes penalized if their journeys exceed a certain number of minutes (Fishman et al., 2013). Some PBSS, including BIXI, Vélib' and DublinBikes, provide an incentive for redistributing bicycles at different docking stations by giving users an extra cost-free 15 min for relocating bicycles from a full station to one with empty racks (Shaheen & Guzman, 2011); so, to a certain extent PBSS users are being given an incentive to lengthen the usual journeys that they make. In this respect, Jurdak (2013) recommends a dynamic price and incentives system that impacts mobility patterns positively, combined with improvements to PBSS planning and management. The price factor might not be a determinant of the distance in our case, the SEVici PBSS, as the free period of public bicycle use is 30 min, which is enough to make long journeys in a medium sized city like Seville. Moreover, the cost of the first hour (once the free first 30 min have been consumed) is €0.51 for members with long duration passes, and €1.03 for those with short duration passes. The penalty for longer journeys therefore does not seem to be significant.

6. Conclusions

Our case study of Seville, where the successful promotion of sustainable and healthy bicycle-based mobility has received considerable international recognition, contributes to the limited literature that analyzes and compares the complex relationship between public and the privately-owned bicycles by focusing on a spatial aspect.

A propensity score matching model has been applied to a database compiled from a survey of PBSS and private bicycle users in Seville with the objective of determining the distances for which each of the bicycle types is more competitive.

In short, bearing in mind the advantages and disadvantages of the two systems, our results point to the private bicycle having a favorable balance of strengths over weaknesses for longer journeys, as it offers greater independence and flexibility, greater comfort and convenience for adapting to greater physical effort, and greater ease of handling. In fact, our findings unequivocally demonstrate that the mean journey length made by private bicycle is between 700 and 800 m (from 0.44 to 0.5 miles) greater than by public bicycle. We then find robust empirical evidence that there is a complementarity relationship between the two modes of transport with respect to distance, and not a substitution relationship, as it is more likely that the public bicycle will be used for shorter distances and the private bicycle for longer distances. In other words, as other research (Castillo-Manzano, Castro-Nuño, & López-Valpuesta, 2015) suggests, the two types of bicycle are compatible with each other and, theoretically, a cyclist could use one or the other, depending on the length of the journey that has to be made. PBSS could therefore represent a permanent and not a transitory optimal alternative, even for people who possess private bicycles.

Notwithstanding, our results should be considered to have been obtained in optimal conditions, given Seville's exceptional geographical and topographical features, and its vast network of bicycle lanes and PBSS docking stations. It would therefore be useful to replicate this study in other cities as a future line of research, as this would enable any of the bias that generally exists -probably in favor of the private bicycle-to be measured in cities where the topography is less benevolent and pedaling therefore requires greater physical effort. This bias would also exist in the unfortunately more common case of cities where PBSS docking stations are fewer and farther between, which would make the public bicycle less competitive.

Focusing on cities' geographical and topographical features, according to our findings PBSS are a more competitive option in small and medium sized cities, where the mean journey length can be expected to be shorter than in large cities. It is therefore not surprising that cities such as Seville itself, and Lyon, have set the international benchmark for these systems. Obviously, these spatial limits are not rigid and can be circumvented by technology. For example, in some cities where distances are greater and/or the terrain is more irregular, i.e., hillier cities, hybrid electric/pedal-powered bicycle public hire systems might be a good alternative. Said bicycles are fitted with an electric motor that makes journeys easier.

The pioneering European capital city of this new model of Public Electric-Bike Sharing Systems (hereinafter PEBSS) is Madrid. However, given how limited its implementation has been in the central area of the city (even though the distance between the northernmost and southernmost bike stations is over 8 km), it would seem that its purpose is to better address the terrain than the greater distances that could be expected in a large city like Madrid. Be that as it may, in light of the serious economic difficulties that the Madrid PEBSS (BiciMAD) is experiencing, PEBSS still do not appear to be a universal solution. In fall 2015, barely a year after having come into operation in June 2014, the managers of the Madrid PEBSS demanded greater subsidies to prevent the system going into more than likely bankruptcy.

Another PEBSS can be added to the example in Madrid, the recently inaugurated Copenhagen Electric-Bike Sharing System. It is still too early to evaluate the success of these systems, but the fact is that the high cost of the bikes and of their maintenance (some $10,000 per bicycle, including the purchase price, for eight years), requires much higher usage fees to be imposed than for traditional non-electric PBSS (specifically, 70DKK/month, i.e., approx. €112.50 per annum, compared to the €33.33 per annum that the Seville PBSS costs, or the Lyon PBSS' €25 per annum or only €15 for young people). In fact, such a large cost difference would also justify the investigation of differences between traditional PBSS and new PEBSS user profiles as a future line of research. Obviously a change in profile could distort any extrapolation of this article's results, as it would change the values of the covariates used (see Table 2). Notwithstanding, it would seem that the city of Rotterdam will be the next to subscribe to this new trend by installing the very same system as Copenhagen.

In our opinion, our findings not only move the literature on PBSS forward in a previously unstudied spatial/geographical aspect, but also contribute to the better organization of PBSS systems. Our results specifically support the need to develop policies −of supply or demand-that reduce the differences between the distances covered by PBSS and private bicycle. Little can be done in the way of demand policy other than extending the traditional 30 min free period offered by PBSS by a few minutes. However, the real effects can be expected to be very limited since, as already stated, the penalty for longer journeys does not seem to be significant for PBSS. A priori, supply policies would seem to be much more pertinent, especially those related to PBSS bicycles' technical features. One interesting line of research that therefore emerges from the results of this study is how to overcome this spatial barrier by improving the technical features of PBSS bicycles and thus improving their competitiveness for longer journeys. Our results would therefore justify any research that improves the speed and ergonomics of public bikes without sacrificing any of the security measures to combat vandalism and theft. Unfortunately, experience shows (see for example Castillo-Manzano & Sánchez-Braza, 2013b) that these security measures, which generally impact public bicycles' competitiveness and appeal, are a necessary condition for PBSS to be able to exist and for preventing a return to the failed beginnings of such systems so plainly illustrated by Amsterdam's White Bicycles.

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Methodological appendix

The first step to implement the proposed methodology is to define a participation indicator of the measure to be evaluated. Thus, starting with a sample of size N, the binary variable $D \in \{0,1\}$ is defined that captures whether individuals have opted to use the PBSS as their mode of urban transport for making a journey ($D_i = 1$), or whether they have made their journeys using their own private bicycles ($D_i = 0$). The sample observations are thus divided into n_1 (participant group) and n_0 (control group).

Next, the response variable Y is defined as the variable on which the causal effect of the measure being analyzed will be evaluated. In this case, variable Y is defined as the length (i.e., the distance in meters) of the journey made by bicycle (public or private), and is defined in terms of the potential results.

$$Y_i \begin{cases} Y_{1i} & if \;\; D_i = 1 \\ Y_{0i} & if \;\; D_i = 0 \end{cases} \tag{1}$$

The measure's causal effect is captured by the difference between the two potential responses: $[Y_{1i}-Y_{0i}]$.

Nevertheless, only one of the two options can be observed for each individual, resulting in what is called the “fundamental problem of causal inference”, which prevents individual causal effects being determined. This makes it necessary to calculate the “Average Treatment Effect on the Treated” (ATET), which could be defined as the difference between the mean values of the response variable for individuals who have used PBSS bicycles and those who have used private bicycles, conditioned on the participant group.

$$ATET = E(Y_1 - Y_0|D = 1) = E(Y_1|D = 1) - E(Y_0|D = 1) \tag{2}$$

However, other variables that could impact on said effect have to be controlled for to obtain the ATET. A k-dimensional vector comprising a set of covariates therefore has to be created. The covariates must be independent of variable D for each and every one of the observations. The condition of independence should therefore be guaranteed that ensures that variable D, which is conditioned on these predetermined variables, is independent of the potential results:

$$D \perp (Y_1, Y_0)|X \tag{3}$$

Thus, the average effect of the PBSS on journey distances made by bicycle is evaluated conditioned on the possible values of the vector of the covariates, X.

This evaluation procedure is a two stage process. The first stage is to calculate the so-called propensity score, called ε(X) and defined as the likelihood that an observation of the sample belongs to the evaluated measure's participant group (in this case, the use of the PBSS), conditioned on the values that a vector X of predetermined covariates adopts.

$$\varepsilon(X) = P(D = 1|X = x) = E[D|X = x] \tag{4}$$

Therefore, calculating the propensity score makes the operation easier when a large number of covariates are involved by reducing these to a single, unidimensional variable. The aforementioned condition of independence is therefore formulated as:

$$D \perp (Y_1, Y_0)|\varepsilon(X) \tag{5}$$

Different binary response models can be used to estimate the propensity score depending on the hypothesis adopted for the form of the distribution function (F).

$$\varepsilon(X) = P(D = 1|X) = F(\beta X) \tag{6}$$

The two most commonly used are the logit and probit models. There is no specific criterion for opting for one model or the other to estimate the propensity score. Generally, the model chosen is that which provides the best results for the maximum log likelihood.

Subsequently, each individual in the participant group with a specific value of ε(X) is assigned one or more individuals from the control group with a value that equates or approximates to ε(X). The distribution of the covariates is thus similar for the two groups. Any possible contamination from the covariates is thus isolated and the result is a non-biased estimator of the evaluated measure.

Once this has been done, the propensity score matching technique is used to calculate the estimator of the ATET using the expression:

$$\widehat{\alpha}_{ATET} = \frac{1}{n_1}\sum_{i=1}^{n_1}\left(Y_i - Y_{m(i)}\right) \tag{7}$$

where $Y_{m(i)}$ is the value of the response variable Y for the control individual assigned as the pair (or the average value, when more than one individual has been assigned) of the participating individual i.

Radius, kernel and stratification matching methods are used for the assignment process. The first of these establishes a radius (r) that enables each participant with a certain propensity score (ε_{i1}) to be assigned all the control individuals with a propensity score (ε_{j0}) within the radius formed by ε_{i1} and r. Thus the pairing condition for the radius method is expressed as:

$$c_{ij} = \left\{\varepsilon_{j_0} \middle| \; \left\|\varepsilon_{i_1} - \varepsilon_{j_0}\right\| < r\right\} \tag{8}$$

where c_{ij} indicates the control individual that meets the pairing condition for individual i.

The kernel matching method, on the other hand, assigns participating individuals a weighted average propensity score for the control individuals within a certain bandwidth (b). The weighting is inversely proportional to the difference in the propensity score between the participant and control individuals. In this case, the weighting term (w) is defined in the following way, where the function k(·) is a kernel function. The Epanechnikov kernel function is applied.

$$w_{ij} = \frac{k\left(\frac{\varepsilon_{i_1}-\varepsilon_{j_0}}{b}\right)}{\sum_{j=1[j\in(D=0)]}^{n_0} k\left(\frac{\varepsilon_{i_1}-\varepsilon_{j_0}}{b}\right)} \tag{9}$$

Finally, the stratification or blocking matching method, which is not dependent upon a caliper radius, divides the range of variation in the propensity score into intervals in such a way that participating and control individuals have similar estimated propensity score values within each interval. Thus, the ATET estimator is calculated as an average of each interval's ATET with weights given by the distribution of participating individuals across intervals.

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