Is e-shopping likely to reduce shopping trips for car owners? A propensity score matching analysis

Abstract: Reducing car use is commonly considered as a potential strategy to reduce transport-related problems such as traffic congestion and air pollution. The increasing use of online shopping may potentially replace shopping trips, thus possibly reducing car use. However, car owners – compared to non-car owners – can more easily visit physical stores and transport goods. Therefore, it can be assumed that online shopping is less likely to reduce shopping trips for car owners. Using 653 structured face-to-face interviews in Chengdu (China), an empirical study is conducted. The results show that 44.0% of respondents indicated a decrease in shopping trip frequency after they started to purchase online, while only 14.4% indicated an increase in the frequency. This confirms that online shopping tends to be a substitute for shopping trips. Applying a propensity score matching approach, this paper further compares the likelihoods of changes in shopping trips caused by online buying between car owners and non-car owners, while considering sociodemographic factors, internet experiences, spatial attributes, and online shopping attitudes as covariates. The results indicate that – due to online buying – shopping trip frequency is less likely to decrease for car owners compared to non-car owners, while there is no significant difference in the likelihood of increasing shopping trip frequency between owners and non-owners. These findings imply that online shopping may not effectively reduce driving, thus unlikely being a valid solution for transportation problems resulting from the increasing use of cars.

Keywords: e-shopping; shopping trips; car ownership; propensity score matching; Chengdu (China)

Highlights

(1) Propensity score matching is applied to infer causality;
(2) Shopping trips can be partly replaced by e-shopping;
(3) E-shopping is less likely to replace shopping trips for car owners;
(4) E-shopping may not effectively reduce driving.

1 Introduction

In the past several decades, car ownership has dramatically increased all over the world (Hickman et al., 2017). The global number of passenger cars reached 947 million by 2015 (OICA, 2016). The great use of cars has caused environmental, transportation, and health challenges in many countries and regions, such as air pollution, fuel consumption, road congestion, parking problems, and obesity (Buehler et al., 2017; Gärling & Steg, 2007; Hickman et al., 2017; Yan et al., 2019). Reducing car use is commonly considered as a possible strategy to mitigate these challenges (De Vos et al., 2012; Graham-Rowe et al., 2011).

E-shopping – as a possible substitute for shopping trips – may potentially reduce car use. Therefore, it is worthwhile to examine whether people who own a car are more likely to replace shopping trips with e-shopping. Theoretically, however, car owners seem less likely to reduce shopping trips due to e-shopping, because they may be more dependent on in-store shopping than non-car owners for the two following reasons. On the one hand, car owners have more mode options to visit physical stores, suggesting a high level of flexibility in shopping trips (e.g., more flexible departure time). On the other hand, car owners can benefit more from driving for in-store shopping, because it is more convenient and effortless to use a car to transport goods home.

To the best of our knowledge, none of the previous empirical studies explicitly aims to investigate whether car owners are more likely to replace shopping trips with e-shopping. Only a few researchers implicitly consider car ownership as one of the explanatory factors for the substitution of e-shopping for shopping trips, however leading to mixed outcomes. For example, a study by Shi et al. (2019) found that e-shoppers who own a car are less likely to consider online buying as a substitute for shopping trips compared to those who do not own a car. In contrast, Weltevreden and Rietbergen (2007) indicated that the likelihood of substituting e-shopping for shopping trips barely differs between car users and non-car users. Xi et al. (2020a) even revealed that people owning a car are more likely to reduce visits to physical stores due to e-shopping.

The mixed findings regarding the role of car ownership in the substitution of e-shopping for shopping trips may be consequences of several factors, such as differences in temporal and geographical contexts of study areas, analysis approaches, and types of products. Specifically, traditional cross-sectional designs (e.g., Chi-square tests, regression approaches) are often used in previous studies. However, the cross-sectional approaches may lead to biased estimates, because all samples are always included in these approaches without consideration of the issue of outliers (Dong, 2021). Therefore, a more appropriate approach for causal inference is called for to clarify the topic. As a quasi-experimental design, the propensity score matching (PSM) method can address sample selection bias by removing outliers and is therefore considered more effective for causal inference than cross-sectional designs (Dong, 2021). In recent years, the PSM method has been introduced to the field of transportation to address some causality issues (Cao & Schoner, 2014; Cheng et al., 2019; Dong, 2021; Kim et al., 2020). However, we cannot find any studies using the PSM method to empirically clarify the issue of how car ownership influences the likelihood to reduce shopping trips due to online buying.

In sum, three limitations exist in previous studies regarding the role of car ownership. First, empirical evidence is still limited. We are only aware of three studies implicitly analyzing this issue (Shi et al., 2019; Weltevreden & Rietbergen, 2007; Xi et al., 2020a). Second, the current evidence suggests inconsistent results. It thus remains unclear whether car owners are more likely or unlikely to replace shopping trips with online shopping. Third, the use of cross-sectional approaches in previous studies may lead to biased estimates, which may be part of the source of inconsistent findings. To address these limitations, the present study using a PSM approach (i.e., a quasi-experimental design) aims to explicitly answer the following question: Is e-shopping likely to reduce shopping trips for car owners?

The data used in the present study are derived from 653 structured face-to-face interviews in 2016 in Chengdu, which is one of the provincial capital cities in China. China has experienced a rapid motorization process in past decades (Zhao & Bai, 2019). In 2000, there were only 6.25 million private cars in China. By the end of 2019, the number has increased to 225 million (CEIC, 2020). The average annual increase rate is approximately 184%. Nonetheless, only 173 out of every 1000 Chinese people owned a car in 2018, which is considerably lower than many countries. In the United States and the United Kingdom, for instance, there are respectively 837 and 579 car owners per thousand people (McKinsey & Company, 2019). Therefore, it can be expected that car ownership in China will continuously and rapidly increase in the coming decades. China must moderate the rapid growth of car use. Meanwhile, e-shopping is widely adopted nowadays in China. Since 2013, the e-retailing sale of China has overtaken that of the United States and has become the largest one in the world (McKinsey & Company, 2016). Therefore, China is a suitable place to investigate the association between car ownership and the reduction in shopping trips caused by online buying.

The remainder of this paper will be organized as follows. In the following section, prior related research is reviewed. In Section 3, methodologies are introduced, followed by analysis results in Section 4. In the final section, conclusions and discussion are presented.

2 Literature review

2.1 Measurement of e-shopping impacts on shopping trips

Researchers have explored the relationship between online shopping and shopping trips for quite a while. In the early stage of e-commerce, it is conceptually proposed that e-shopping has four potential effects on shopping trips. They respectively mean that, due to online buying, people can reduce shopping trips (i.e., substitution), increase shopping trips (i.e., complementarity), change the attributes of shopping trips (i.e., modification), or do not make any changes to shopping trips (i.e., neutrality) (Mokhtarian, 1990; Salomon, 1986). Subsequently, much scholarly attention has been paid to empirically examine the influence of e-shopping on shopping trips. However, previous studies lead to inconsistent results respectively confirming substitution effect, complementary effect, modification effect, and neutrality effect (Cao, 2009; Rotem-Mindali & Weltevreden, 2013; Xi et al., 2020b).

The mixed findings regarding the relationship between online buying and shopping trips may be attributed to several reasons, such as variations in the geographical and temporal contexts of study areas. In addition, some researchers particularly note that the inconsistency might be the result of differentiated measuring methods (Cao, 2009; Rotem-Mindali & Weltevreden, 2013; Shi et al., 2019; Xi et al., 2020a). Overall, two designs are most used to capture the impacts of e-shopping on shopping trips in existing studies. One is a cross-sectional design. In this design, researchers usually obtain the frequencies of both e-shopping and shopping trips and identify the quantitative association between them using statistical techniques such as regression models and structural equation models (e.g., Ding & Lu, 2017; Zhen et al., 2016; Zhou & Wang, 2014). The other is a quasi-longitudinal design, in which respondents are asked to recall and directly indicate the changes in shopping trips before and after buying online. The changes are considered as the effects of e-shopping on shopping trips (e.g., Weltevreden & Rietbergen, 2007; Xi et al., 2020a).

However, the problem is that results seem to largely depend on the measurement approaches. Shi et al. (2019) summarized that cross-sectional analyses usually support that e-shopping tends to generate new shopping trips (i.e., complementary effect) (e.g., Ding & Lu, 2017; Zhen et al., 2016; Zhou & Wang, 2014), while quasi-longitudinal designs normally confirm that e-shopping likely replaces shopping trips (i.e., substitution effect) (e.g., Shi et al., 2019; Weltevreden & Rietbergen, 2007; Xi et al., 2020a). It is widely accepted that – compared to a cross-sectional design – a quasi-longitudinal design is more reliable to infer causality (Mokhtarian & Cao, 2008). Furthermore, Xi et al. (2020a) simultaneously used both cross-sectional and quasi-longitudinal designs to examine the influence of e-shopping on shopping trips. Not surprisingly, the two approaches indicate inconsistent results. Nonetheless, they supposed that the quasi-longitudinal results (i.e., substitution effect) are more reliable than the cross-sectional results (i.e., complementary effect).

In addition, quasi-longitudinal designs have an advantage over cross-sectional designs. Using a quasi-longitudinal method, a change in shopping trip frequency caused by e-shopping can be captured for each respondent. Thus, it provides a possibility to investigate the determinants of changes in shopping trips due to e-shopping (Weltevreden & Rietbergen, 2007; Xi et al., 2020a), e.g., the focus of the present study – the effects of car ownership on changes in shopping trips. Therefore, we will apply a quasi-longitudinal design to measure changes in shopping trips due to online shopping in the present study.

2.2 Car ownership and the substitution of e-shopping for shopping trips

Investigating the relationship between car ownership and the reduction in shopping trips caused by online buying can contribute valuable insights to the existing literature. To the best of our knowledge, however, little research has fully explored this topic. There are only a few researchers who preliminarily considered it, whereas inconsistent results are found.

Using 3200 respondents in the Netherlands, a study by Weltevreden and Rietbergen (2007) was the first to investigate this issue. They found that more than 20% of the respondents indicate a decrease in shopping trips because of online buying. Applying a Chi-square test, they revealed that there is no significant difference in changes in shopping trips between car users and non-car users. This means that – like non-car users – car users tend to reduce shopping trips due to e-shopping, potentially suggesting that e-shopping may reduce driving.

A recent study by Xi et al. (2020a) further explored the relationship between car ownership and the substitution of e-shopping for shopping trips. In their study, the data were obtained from a retrospective survey including 1207 valid respondents in Nanjing, China. Similarly, they indicated that – due to e-shopping – e-shoppers are likely to report decreasing in-store shopping frequency. Meanwhile, using an ordinal logistic regression model, they found that e-shoppers who own a car are more likely to reduce visits to supermarkets due to online buying. Therefore, this further suggests that e-shopping may lead to a considerable reduction in driving.

However, the idea that e-shopping can reduce driving seems counterintuitive (Xi et al., 2020a), because compared to non-car owners, car owners have more convenience to visit stores and transport goods and are thus less likely to consider online buying as a substitute for shopping trips. An empirical study by Shi et al. (2019) pointed to a different story from both Weltevreden and Rietbergen (2007) and Xi et al. (2020a). Using data derived from 710 face-to-face interviews in Chengdu, China, they similarly confirmed online shopping as a substitute for shopping trips. However, a binary logistic regression model shows that car ownership is negatively correlated with the substitution of e-shopping for shopping trips, which means that car owners are unlikely to reduce shopping trips when purchasing online.

Apparently, previous studies suggest conflicting results concerning the relationship between car ownership and changes in shopping trips due to e-shopping. This might be attributed to some factors including variations in geographical and temporal contexts and in types of products in these studies. Notably, the approaches used in these studies could be another source of the inconsistent results as well. Chi-square tests (Weltevreden & Rietbergen, 2007), ordinal logistic models (Xi et al., 2020a), and binary logistic models (Shi et al., 2019) developed with cross-sectional data can generally be categorized as traditional cross-sectional analyses. In these traditional cross-sectional approaches, it is implicitly assumed that samples are randomly selected. In practice, however, it is hard to obtain samples without any selection bias (i.e., outliers are mostly included). Therefore, these traditional cross-sectional approaches may result in biased estimation outcomes for causality inference.

In order to overcome the limitation of traditional cross-sectional designs, propensity score matching (PSM) – which is often considered as a quasi-experimental design (Kim et al., 2020; Park et al., 2020) – is introduced to infer causality by transportation researchers (Boer et al., 2007; Dill, 2008). In PSM, outliers are eliminated according to propensity scores, thus possibly correcting selection bias (Dong, 2021; Kim et al., 2020). Therefore, the PSM method is usually considered more reliable for causal inference than traditional cross-sectional methods (Dong, 2021). In recent years, researchers have increasingly used a PSM approach to address some transportation issues (e.g., residential self-selection) (Cheng et al., 2019; Cao & Schoner, 2014). However, little research can be found to apply a PSM approach to infer the causality between car ownership and the reduction in shopping trips caused by online shopping. Therefore, a PSM method will be used in the present study to clarify whether car owners are likely or unlikely to substitute e-shopping for shopping trips.

In addition to car ownership, other factors including sociodemographic factors, internet experiences, e-shopping attitudes, and built environment elements are found to be associated with the likelihood of substituting e-shopping for shopping trips (Shi et al., 2019; Weltevreden & Rietbergen, 2007; Xi et al., 2020a). Therefore, these factors will be considered as control variables (i.e., covariates) in the PSM design of the present study.

3 Analysis design

3.1 Data source

The data used in this study are mainly generated from face-to-face structured interviews in 2016 in Chengdu, China. In this survey, e-shoppers – those who had ever purchased online before – were regarded as the target population. Following the principle of a cluster sampling approach (Daniel, 2011), we geographically randomly selected 10 public spaces as the sampled units: Chunxilu Shopping Center, Hongpailou Shopping Center, Huanhuaxi Park, Jinniu-Wanda Shopping Center, Tianfu Square, Laifushi Shopping Center, Dongjiaojiyi Music Park, Tazishan Park, Shahe Park, and Kaide Shopping Center (see Figure 1). Participants were recruited using the convenience sampling method, which means that residents who were readily available in these public spaces and had ever purchased online (i.e., e-shoppers) were approached. For each participant, a face-to-face interview was conducted by asking questions concerning sociodemographics, internet experiences, spatial attributes, and e-shopping attitudes. Finally, 1796 residents were invited, and 882 participated in the survey. After removing records missing information, a total of 653 valid respondents are used in the present study. More details concerning the survey can be found in ** (BLINDED FOR PEER REVIEW).

Only online buyers are used as valid respondents in the present study. This makes it hard to assess the representativeness of these respondents because the attributes of the online buying population in Chengdu are unknown. A survey performed by the China E-commerce Research Center (2016) showed that in China 47.4% of online buyers were male, and 48.8% were aged 27 or older in 2016. Of 653 valid participants in the present study, 51.1% are male, and 42.4% are aged 26 or older. Based on the comparison concerning gender and age, the representativeness of the respondents can be considered acceptable.

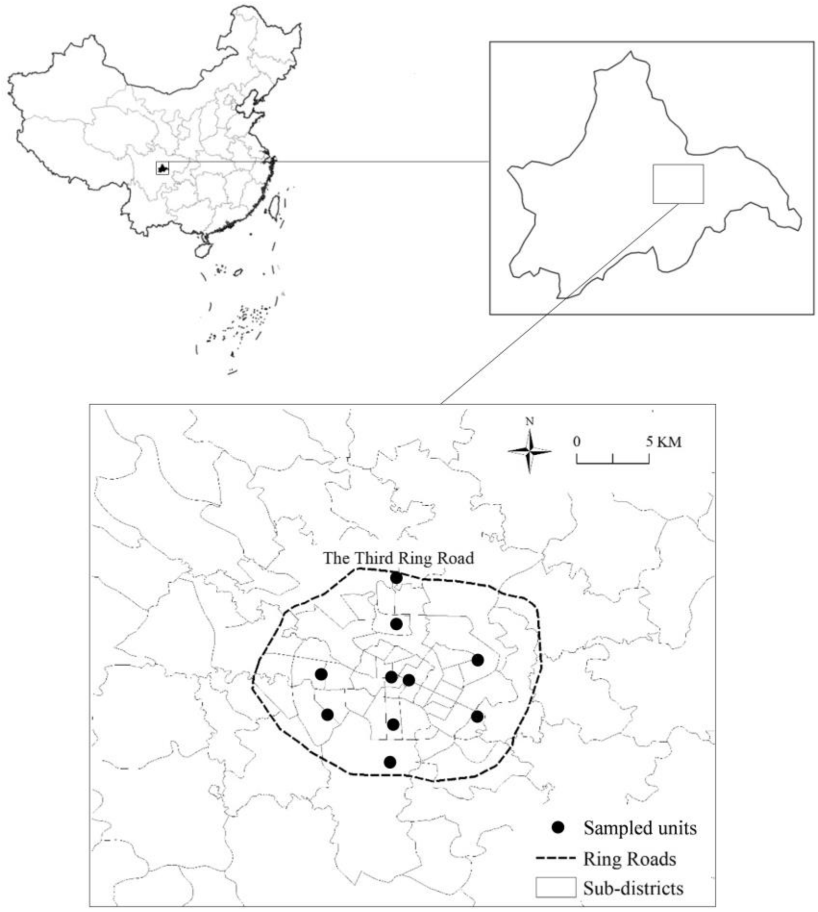

Figure 1. Sampled units in Chengdu, China (Source: BLINDED FOR PEER REVIEW)

3.2 Key variables

3.2.1 E-shopping impacts on shopping trips

As indicated before, the key dependent variable – e-shopping impacts on shopping trip frequency – is acquired by using a quasi-longitudinal method. In face-to-face interviews, respondents were asked to recall and report the changes in shopping trip frequency after starting to shop online. In the end, 287, 272, and 94 respondents indicated a decrease, no change, and an increase in the frequency of shopping trips, respectively. This means that e-shopping seems substitute for shopping trips, because 44.0% of respondents reported a reduction in shopping trip frequency, and only 14.4% reported an increase (see Table 1). This result is consistent with most previous quasi-longitudinal studies (e.g., Weltevreden & Rietbergen, 2007; Xi et al., 2020a).

The impacts of e-shopping on shopping trips are measured by three categories (i.e., decrease, no change, and increase), which can be treated as a nominal variable.

However, the PSM method cannot be directly used for a nominal outcome variable. To address this issue, three dummy variables were created, i.e., “decrease” (0 = no decrease; 1 = decrease), “no change” (0 = decrease/increase; 1 = no change), and “increase” (0 = no increase; 1 = “increase”), which will be separately used as outcome variables in the following PSM analysis.

3.2.2 Car ownership

As another key variable, car ownership can normally be measured in two possible ways: household car ownership and individual car ownership. When a household owns a car, the car is mostly shared among household members. This means that car dependence is mainly determined by household car ownership rather than individual car ownership. Therefore, it can be reasonably assumed that household car ownership has higher explanation power for travel. Given this, car ownership is obtained by asking respondents: Does your household own a private car? The answer was set to be “Yes” or “No”. Among 653 valid records, 400 answered “Yes”, and 253 answered “No” (see Table 1).

3.3 Control variables

Following previous studies (Shi et al., 2019; Weltevreden & Rietbergen, 2007; Xi et al., 2020a), four sets of control variables are used in the present study. The first set refers to sociodemographic factors including gender, age, educational attainment, monthly income, and monthly living cost. The second set is internet experience which consists of two variables. One is the number of years using the internet on PCs. The other is the monthly frequency (i.e., times per regular month) of e-shopping for goods that are most purchased online, including food and drink, electronics, clothes and shoes, and cosmetics.

The third set refers to built environment elements. Shopping trips are usually linked with trips for other purposes such as commuting. This means that people may not depart for shopping trips from residential locations. Therefore, the built environment of departure locations for shopping trips (instead of residential locations) was recommended as an explanatory factor in recent publications (Shi et al., 2020a, 2020b). For each respondent, we acquired the location where he/she mostly departs from for shopping trips in the survey. Using departure locations, we identify the built environment for each respondent. Notably, according to previous studies (Loo & Wang, 2018; Weltevreden & Rietbergen, 2007; Xi et al., 2020a; Zhen et al., 2018), both city-level and neighborhood-level built environment elements are considered in the present study:

- At the city level, respondents are divided into two groups, namely, urban group and suburban group. When a respondent mostly departs for shopping trips from the densely built-up areas within the third ring road of Chengdu (see Figure 1), he/she will be categorized into the urban group. Otherwise, he/she will be categorized into the suburban group.
- At the neighborhood level, shopping accessibility and transport accessibility – which are frequently used as explanatory factors for e-shopping (e.g., Loo & Wang, 2018; Weltevreden & Rietbergen, 2007) – are employed. In the present study, shopping accessibility is indicated by the number of supermarkets within a buffer distance of 800 m of departure locations. Transport accessibility is measured by the number of bus stops within a buffer distance of 800 m of departure locations. The buffer distance is set to 800 m because it is the maximum distance of access trips by walking for most residents in large Chinese cities (Pan et al., 2010).

The fourth set refers to e-shopping attitudes. According to Shi et al. (2020a), respondents were asked to rate ten statements in the interviews (see Table 2). The answers range from “strongly disagree (value=1)” to “strongly agree (value=5)”. To reduce the dimensions of the attitudes, a principal axis factor analysis with Promax rotation is applied to extract three factors. 42.4% of the total extracted variances are explained by the three factors. The pattern matrix is reported in Table 2.

Table 1. Descriptions of variables (N=653)

Variables	Descriptions	Frequency /Mean	Percentage /S.D.
Changes in trip frequency	Decrease	287	44.0%
	No change	272	41.7%
	Increase	94	14.4%
Car ownership	Yes	400	61.3%
	No	253	38.7%
Sociodemographics			
Gender	Male	334	51.1%
	Female	319	48.9%
Age (Years)	20 or younger (Value=1)	166	25.4%
	21-25 (Value=2)	210	32.2%
	26-30 (Value=3)	157	24.0%
	Older than 30 (Value=4)	120	18.4%
Education	High school or less (Value=1)	125	19.1%
	Colleges or technical school (Value=2)	118	18.1%
	Undergraduate school (Value=3)	345	52.8%
	(Post-) graduate school (Value=4)	65	10.0%
Monthly income (Yuan)	1000 or less (Value=1)	186	28.5%
	1001-4000 (Value=2)	209	32.0%
	4001-8000 (Value=3)	197	30.2%
	More than 8000 (Value=4)	61	9.3%
Monthly living cost (Yuan)	1000 or less (Value=1)	94	14.4%
	1001-2000 (Value=2)	249	38.1%
	2001-4000 (Value=3)	231	35.4%
	More than 4000 (Value=4)	79	12.1%
Internet experiences			
Years of using internet on PCs	No more than 5 (Value=1)	98	15.0%
	6-9 (Value=2)	295	45.2%
	More than 9 (Value=3)	260	39.8%
E-shopping frequency	E-shopping frequency per regular month	8.76	8.48
Built environment elements			
Urban areas	Departure locations within the 3^{rd} ring road	317	48.5%
Suburban areas	Departure locations outside the 3^{rd} ring road	336	51.5%
Accessibility to supermarkets	Number of supermarkets within a buffer distance of 800 m	35.38	20.55
Accessibility to bus stations	Number of bus stations within a buffer distance of 800 m	13.20	8.57

Note: S.D. = Standard deviation.

Table 2. Pattern matrix of the factor analysis

Factors	Statements	Loadings
Satisfaction	I feel more satisfied with e-shopping than in-store shopping	0.68
	I am pleased to recommend e-shopping to my friends or relatives	0.64
	I can find high-quality goods online	0.60
	I feel overall satisfied with e-shopping	0.58
	E-shopping is recommended by my friends or relatives	0.51
Convenience	It is convenient to pay for goods online	0.74
	I can find a large variety of goods online	0.66
	E-shopping is flexible because I can buy online at any time	0.51
Low prices	E-shopping is a strategy of reducing trips	0.76
	The prices of online goods are low	0.59

3.4 Analysis approach

In the present study, a propensity score matching (PSM) is applied in the following three steps. First, the propensity score is calculated using a binary logistic regression model (Cao & Schoner, 2014; Cheng et al., 2019). In the binary logistic model, car ownership is employed as the dependent variable, and control variables (i.e., covariates) including sociodemographic factors, internet experiences, built environment elements, and e-shopping attitudes are used as independent variables. Considering that the built environment at the city level and at the neighborhood level may be strongly correlated with one another, they are separately included when calculating propensity scores.

Second, we performed the matching for each respondent according to the propensity score. Before matching, respondents who own a car are categorized as a treatment group, and those who do not are categorized as a control group. Following the principle of the nearest neighbor, each respondent is matched to one from a different group (i.e., 1:1 matching). This means that, for instance, a respondent from the treatment group (i.e., a car owner) is matched to the one who is from the control group (i.e., a non-car owner) and has the nearest propensity score, and vice versa. In theory, it is considered “identical” and comparable between two matched respondents (Cheng et al., 2019).

Third, the effects of car ownership on changes in shopping trips caused by online buying are estimated in the following three ways (Heinrich et al., 2010).

- The Average Treatment Effect on the Treated (ATT):

$$ATT=E(Y_1-Y_0|D=1) \quad (1)$$

- The Average Treatment Effect on the Untreated (ATU):

$$ATU=E(Y_1-Y_0|D=0) \tag{2}$$

- The Average Treatment Effect (ATE) across all respondents:

$$ATE=E(Y_1-Y_0) \tag{3}$$

Where D=1 refers to respondents owning a car (i.e., car owners), and D=0 refers to respondents not owning a car (i.e., non-car owners); Y_1 represents the likelihood of changes in shopping trip frequency caused by e-shopping for car owners, and Y_0 represents the likelihood of changes in shopping trip frequency caused by e-shopping for non-car owners. Accordingly, ATT indicates an average counterfactual difference in the likelihood of changes in shopping trip frequency caused by e-shopping between car owners and matched non-car owners. ATU is an average counterfactual difference in the likelihood of changes in shopping trip frequency caused by e-shopping between non-car owners and matched car owners. ATE refers to an average counterfactual difference in the likelihood of changes in shopping trip frequency caused by e-shopping between all respondents and matched respondents, which can be understood as the effect combining ATT and ATU.

4 Results

4.1 Preliminary results

Applying a simple descriptive analysis, we preliminarily compare the likelihoods of changes in shopping trip frequency due to online shopping between car owners and non-car owners without consideration of other relevant factors. The results in Table 3 show that 41.5% of car owners and 47.8% of non-car owners respectively reported decreasing shopping trips after starting shopping online. This means that – compared to car owners – non-car owners may overall have a 6.3% higher likelihood to reduce shopping trips due to e-shopping. Meanwhile, the frequency of shopping trips seems more likely to remain the same for car owners (46.8%) compared to non-car owners (33.6%). A higher proportion of non-car owners (18.6%) indicated an increase in shopping trip frequency than did car owners (11.8%). A Chi-square test suggests that the likelihood difference is statistically significant (χ^2=12.9, Sig.=0.02).

However, the simple descriptive analyses ignore the potential influence of other factors such as sociodemographic factors, internet experiences, e-shopping attitudes, and built environment elements. More importantly, as a traditional cross-sectional method, the simple statistical analyses do not exclude outliers to reduce possible sample selection bias, which may lead to biased estimates. Therefore, the preliminary results are not reliable enough. In the following PSM analyses, taking these potentially relevant factors into account and removing possible outliers, the relationship between car ownership and changes in shopping trip frequency due to online shopping will be more precisely estimated.

Table 3. Chi-square test for the substitution effects of e-shopping on shopping trips

Groups	Decrease		No change		Increase		Chi-square test
	N	%	N	%	N	%	
Car owners	166	41.5	187	46.8	47	11.8	χ^2=12.9
Non-car owners	121	47.8	85	33.6	47	18.6	Sig.=0.02
Total	287	44.0	272	41.7	94	14.4	

4.2 PSM results

In this section, the results of PSM analyses are presented and discussed. As mentioned before, propensity scores are computed twice because the built environment at the city level and at the neighborhood level is separately taken into account. As a result, the matching is correspondingly performed twice. After matching, it is an essential assumption in PSM that all covariates are balanced between the treatment group and the control group. When only using the principle of the nearest neighbor for matching, a balance check shows significant differences in some covariates between the two groups. This suggests that the assumption is violated. In order to handle this issue, a caliper width is additionally introduced to the matching process. When the caliper width is set to 0.002[1], all covariates are insignificantly different between the treatment group and the control group after matching according to t-tests (see Table 4). Furthermore, a standardized difference is calculated for each covariate according to Cheng et al. (2019). The results show that standardized differences of all covariates are lower than ±10% (see Table 4). Meanwhile, the overall standardized differences of both matchings are no more than 25%, and the overall ratios equal approximately one. These results suggest that well-balanced matchings are developed in the present study (Cheng et al., 2019; Zhou & Wang, 2019). The assumption of PSM is supported well. In the end, when built environment elements at the city level and at the neighborhood level are considered, a total of 529 and 519 pairs of respondents are successfully obtained, respectively.

[1] This means that the difference in propensity scores between two matched individuals is lower than 0.2%.

Table 4. Balance check with t-test and standardized differences

Variables	Before matching				After matching (1:1 matching)							
	Mean		p	S.D.	Mean		p	S.D.	Mean		p	S.D.
	TG	CG	(Diff.)		TG	CG	(Diff.)		TG	CG	(Diff.)	
Sociodemographics												
Gender (Female=ref.)	0.50	0.54	0.290	-8.5	0.52	0.51	0.871	1.3	0.52	0.48	0.298	8.4
Age	2.38	2.31	0.380	7.3	2.36	2.32	0.602	4.2	2.32	2.23	0.265	8.8
Education	2.62	2.40	0.002	24.8	2.58	2.54	0.589	4.4	2.55	2.48	0.331	7.9
Income	2.24	2.14	0.194	10.8	2.25	2.19	0.453	6.1	2.20	2.22	0.766	-2.4
Living cost	2.60	2.22	0.000	44.8	2.50	2.47	0.663	3.5	2.49	2.52	0.575	-4.5
Internet experiences												
Years of using internet on PCs	2.36	2.07	0.000	42.9	2.28	2.32	0.426	-6.3	2.30	2.31	0.809	-1.9
E-shopping frequency	8.65	8.93	0.678	-3.3	8.77	9.07	0.682	-3.4	8.79	8.52	0.703	3.1
E-shopping attitudes												
Satisfaction	-0.07	0.11	0.010	-21.0	-0.02	0.04	0.382	-7.0	0.00	0.08	0.220	-9.5
Convenience	-0.01	0.01	0.823	-1.8	0.00	0.02	0.796	-2.1	0.02	0.04	0.697	-3.1
Low prices	0.02	-0.02	0.558	4.7	0.01	0.01	0.974	0.3	0.01	0.02	0.849	-1.5
Built environment elements												
Urban areas (Suburban areas=ref.)	0.50	0.47	0.540	4.9	0.51	0.48	0.465	6.0				
Accessibility to bus stations	13.50	12.72	0.259	9.2					13.24	12.86	0.569	4.5
Accessibility to supermarkets	35.68	34.92	0.646	3.6					35.56	34.24	0.422	6.3

Note: TG = Treatment group, CG = Control group; p values are computed by t-test; S.D.=Standardized differences.

Using formulas (1)~(3), ATT, ATU, and ATE are computed, respectively. In initial results, the standard error and the significance level are reported only for ATT. In order to precisely assess ATT, ATU, and ATE, a bootstrapping method is used to estimate their bias-corrected standard errors and significance levels. The number of replicates in the bootstrap process is set to 1000.

Table 5 shows the PSM outcomes when the city-level built environment is considered. Regarding the decrease in shopping trip frequency, ATT is estimated to be -0.099, which is statistically significant ($p<0.10$) before bootstrapping but insignificant ($p>0.10$) after bootstrapping. This suggests that the likelihood of reducing shopping trips for car owners is 9.9% lower than that for matched non-car owners. ATU is estimated to be -0.154, which is significant at $p<0.05$ after bootstrapping. This means that the likelihood of reducing shopping trips for matched car owners is 15.4% lower than that for non-car owners. In addition, ATE is estimated to be -0.123, which is at a significance level of $p<0.05$ after bootstrapping. This means that – overall – owning a car would decrease the likelihood of substituting e-shopping for shopping trips by 12.3%.

For no change in shopping trip frequency, ATT is estimated to be 0.152, which is statistically significant both before ($p<0.01$) and after bootstrapping ($p<0.05$). This suggests that the likelihood of shopping trips remaining the same after the adoption of e-shopping for car owners is 15.2% higher than that for matched non-car owners. ATU is estimated to be 0.207, which is significant at $p<0.01$ after bootstrapping. This implies that the likelihood of shopping trips remaining the same after the adoption of e-shopping for matched car owners is 20.7% higher than that for non-car owners. Additionally, ATE is estimated to be 0.176 with a significance level of $p<0.01$ after bootstrapping. Overall, this suggests that owning a car would decrease the likelihood of changing shopping trips by 17.6%.

Concerning the increase in shopping trip frequency, ATT, ATU, and ATE are all estimated to have an insignificant value of -0.053 ($p>0.10$). This suggests that the likelihood of increasing shopping trips due to e-shopping barely differs between car owners and non-car owners.

Table 5. The average effects when considering city-level built environment

Changes in trip frequency	Effects	Coefficients	S.E.	Bias-corrected S.E.
	ATT	-0.099	0.054*	0.067
Decrease	ATU	-0.154	N.A.	0.072**
	ATE	-0.123	N.A.	0.059**
	ATT	0.152	0.052***	0.063**
No change	ATU	0.207	N.A.	0.069***
	ATE	0.176	N.A.	0.056***
	ATT	-0.053	0.040	0.050
Increase	ATU	-0.053	N.A.	0.050
	ATE	-0.053	N.A.	0.041

Note: * p<0.10, ** p<0.05, *** p<0.01; N.A.= Not applicable; S.E. = Standard error.

Table 6 displays the estimated results of ATT, ATU, and ATE when the neighborhood-level built environment is considered. Overall, the estimated influence of car ownership on the decrease and no change in shopping trips are consistent with results shown in Table 5, although the magnitudes are slightly different. Therefore, it can be concluded that – due to online buying – car owners are less likely to reduce but more likely to remain their frequencies of shopping trips compared to non-car owners. Interestingly, the estimated ATU and ATE regarding the increase in shopping trips are both negative and statistically significant ($p<0.10$). This result is not fully in line with Table 5. Importantly, the ATU and ATE levels are only marginally significant (both at $p = 0.098$). Therefore, it can hardly be concluded that car owners have a lower likelihood to increase shopping trip frequency than do non-car owners.

Table 6. The average effects when considering neighborhood-level built environment

Changes in trip frequency	Effects	Coefficients	S.E.	Bias-corrected S.E.
	ATT	-0.135	0.056**	0.072*
Decrease	ATU	-0.082	N.A.	0.070
	ATE	-0.114	N.A.	0.060*
	ATT	0.193	0.053***	0.070***
No change	ATU	0.163	N.A.	0.071**
	ATE	0.181	N.A.	0.060***
	ATT	-0.058	0.042	0.049
Increase	ATU	-0.082	N.A.	0.049*
	ATE	-0.067	N.A.	0.041*

Note: * p<0.10, ** p<0.05, *** p<0.01; N.A.= Not applicable; S.E. = Standard error.

Given that the results in Tables 5 and 6 are not fully consistent (particularly regarding the increase in shopping trips), a sensitivity test is needed to check the robustness of these results. According to Heinrich et al. (2010), we perform a robustness check by adjusting matching algorithms. Normally, the number of nearest neighbors used for matching usually ranges from 1 to 4 in a PSM analysis. In the above analyses, only the method of 1:1 matching (i.e., the number of nearest neighbors for matching equals 1) is applied. For a robustness check, the number of nearest neighbors for matching is now set to 2, 3, and 4 (i.e., 1:2 matching, 1:3 matching, and 1:4 matching), respectively.

Similarly, the caliper width is always set to 0.002 in the following matching processes. This also leads to 529 respondents that are successfully matched to others when the city-level built environment is considered (see Table 7) and 519 respondents that are successfully matched to others when the neighborhood-level built environment is considered (see Table 8). T-tests and standardized differences are further used to check the balance between control groups and treatment groups after matching. The results reported in Appendix A and B indicate that all covariates are insignificantly different between treatment groups and control groups after matching. At the same time, all overall standardized differences are no more than 25%, and all overall ratios equal approximately one.

When the number of nearest neighbors for matching is respectively set to 2, 3, and 4 – as shown in Tables 7 and 8 – all ATT, ATU, and ATE regarding the decrease and no change in shopping trip frequency are always estimated to be negative, mostly at significant levels ($p<0.10$, $p<0.05$, or $p<0.01$). In particular, ATE (assessing the overall treatment effects) is always statistically significant ($p<0.10$, $p<0.05$, or $p<0.01$). The results repeatedly point to a similar story that – after the adoption of online buying – the frequency of shopping trips is less likely to decrease but more likely to remain the same for car owners compared to non-car owners.

The effects of car ownership on the increase in shopping trips are, however, always statistically insignificant ($p>0.10$) when the number of nearest neighbors for matching is set to 2, 3, or 4 (Tables 7 and 8). It can therefore be interpreted that the likelihood of increasing shopping trip frequency caused by online purchases is not significantly different between car owners and non-car owners.

Finally, we compare the PSM analyses in Tables 5-8 and the descriptive analyses in Table 3. Overall, both outcomes show similar trends concerning the effects of car ownership on changes in shopping trip frequency due to online buying. However, there are differences between them in the magnitude of the effects. In particular, owning a car can reduce the likelihood of the substitution of online buying for shopping trips by 7.8% - 17.2% according to the PSM analyses, but only by 6.3%

according to the descriptive analyses. As discussed above, it can be assumed that the PSM results are more reliable than the descriptive results because the former are estimated after excluding outliers and considering the influence of covariates. Therefore, compared to the PSM outcomes, the descriptive outcomes to some extent underestimate the magnitude of the negative effects of car ownership on the substitution of e-shopping for shopping trips.

Table 7. Robustness check when considering city-level built environment

Matching methods	Changes in trip frequency	Effects	Coefficients	S.E.	Bias-corrected S.E.
1:2 matching (N=529)	Decrease	ATT	-0.093	0.051*	0.064
		ATU	-0.172	N.A.	0.068**
		ATE	-0.127	N.A.	0.058**
	No change	ATT	0.139	0.049***	0.061**
		ATU	0.227	N.A.	0.066***
		ATE	0.177	N.A.	0.054***
	Increase	ATT	-0.046	0.037	0.047
		ATU	-0.055	N.A.	0.048
		ATE	-0.050	N.A.	0.041
1:3 matching (N=529)	Decrease	ATT	-0.079	0.051	0.063
		ATU	-0.148	N.A.	0.067**
		ATE	-0.108	N.A.	0.058*
	No change	ATT	0.134	0.049***	0.060**
		ATU	0.208	N.A.	0.065***
		ATE	0.165	N.A.	0.055***
	Increase	ATT	-0.055	0.037	0.046
		ATU	-0.060	N.A.	0.047
		ATE	-0.057	N.A.	0.040
1:4 matching (N=529)	Decrease	ATT	-0.078	0.051	0.063
		ATU	-0.146	N.A.	0.066**
		ATE	-0.107	N.A.	0.057*
	No change	ATT	0.134	0.049***	0.060**
		ATU	0.204	N.A.	0.064***
		ATE	0.164	N.A.	0.054***
	Increase	ATT	-0.056	0.038	0.045
		ATU	-0.059	N.A.	0.047
		ATE	-0.057	N.A.	0.040

Note: * p<0.10, ** p<0.05, *** p<0.01; N.A.= Not applicable; S.E. = Standard error.

Table 8. Robustness check when considering neighborhood -level built environment

Matching methods	Changes in trip frequency	Effects	Coefficients	S.E.	Bias-corrected S.E.
1:2 matching (N=519)	Decrease	ATT	-0.140	0.053***	0.070**
		ATU	-0.079	N.A.	0.067
		ATE	-0.116	N.A.	0.060*
	No change	ATT	0.172	0.051***	0.067**
		ATU	0.154	N.A.	0.068**
		ATE	0.165	N.A.	0.059***
	Increase	ATT	-0.032	0.039	0.047
		ATU	-0.075	N.A.	0.047
		ATE	-0.049	N.A.	0.040
1:3 matching (N=519)	Decrease	ATT	-0.141	0.052***	0.069**
		ATU	-0.090	N.A.	0.066
		ATE	-0.120	N.A.	0.059**
	No change	ATT	0.185	0.050***	0.066***
		ATU	0.159	N.A.	0.067**
		ATE	0.174	N.A.	0.059***
	Increase	ATT	-0.044	0.039	0.047
		ATU	-0.069	N.A.	0.046
		ATE	-0.054	N.A.	0.040
1:4 matching (N=519)	Decrease	ATT	-0.145	0.052***	0.068**
		ATU	-0.097	N.A.	0.065
		ATE	-0.126	N.A.	0.059**
	No change	ATT	0.188	0.050***	0.066***
		ATU	0.164	N.A.	0.066**
		ATE	0.178	N.A.	0.058***
	Increase	ATT	-0.042	0.039	0.046
		ATU	-0.067	N.A.	0.045
		ATE	-0.052	N.A.	0.040

Note: * p<0.10, ** p<0.05, *** p<0.01; N.A.= Not applicable; S.E. = Standard error.

5 Conclusions and discussion

Using data acquired from 653 face-to-face structured interviews in 2016 in Chengdu, China, the present study employs a propensity score matching (PSM) approach to capture the association between car ownership and changes in shopping trip frequency caused by e-shopping. The analyses can contribute to the existing literature in two aspects. First, different from most previous studies on e-shopping impacts on shopping trips for the general e-shopping population (e.g., Ding & Lu, 2017; Zhen et al., 2016; Weltevreden & Rietbergen, 2007), the present study focuses on a special group, i.e., car owners, who play a critical role in transportation systems. This can provide novel knowledge on how e-shopping impacts shopping trips for car owners, thus yielding practical implications for transportation systems. Second, mostly employing traditional cross-sectional analyses (e.g., regression approaches with cross-sectional data), previous studies lead to mixed findings regarding the role of car ownership in changes in shopping trip frequency due to online buying. In the present study, a quasi-experimental design (i.e., PSM) is applied, which can better capture a causality relationship than a traditional cross-sectional design (Dong et al., 2021).

The analyses show that 44.0% of respondents indicated a reduction in shopping trip frequency after starting to purchase online. Therefore, it can be concluded that e-shopping tends to be a substitute for shopping trips. Notably, however, only online buyers are considered as the target population in the present study. In China, 485.4 million people were online buyers in 2017, accounting for 44.3% of the total population (E-Marketer, 2018). In other words, more than half (55.7%) of Chinese people had never purchased online, meaning that e-shopping can hardly impact shopping travel for them. If the respondents used in the present study were recruited without sample selection bias, it can be roughly estimated that only around 19.5%[2] of the total population reduce shopping trips due to e-shopping in China. Therefore, e-shopping may not alleviate shopping travel demands as effectively as expected even when e-shopping can partly replace shopping trips. More importantly, the PSM outcomes suggest that the likelihood to substitute e-shopping for shopping trips is lower for car owners than non-car owners. This implies that e-shopping may have a limited substitution effect on driving, thus unlikely mitigating transportation problems caused by increased car use, e.g., road congestion. From a new perspective, the conclusions partly answer the question raised by Mokhtarian (2009, in the title) –

[2] Around 44.3% of the total population were e-shoppers, of which 44.0% indicated substituting e-shopping for shopping trips. Therefore, 44.3%*44.0%≈19.5% of the total population reduced shopping trips due to e-shopping.

“if telecommunication is such a good substitute for travel, why does congestion continue to get worse?”.

Furthermore, the extent to which car ownership influences the substitution of e-shopping for shopping trips may differ in various parts of the world. According to OICA (2015), 78%, 63%, 56%, and 48% of respondents from Africa, America, Europe, and Asia indicated that they cannot imagine living their life without cars, respectively. This suggests a considerable variation in the dependence on private cars by these regions. In particular, the lowest dependence exists in Asian countries like China, and higher dependence exists in Africa and America. Taking Chengdu (China) as the study area, the present study suggests that e-shopping has a limited substitution effect on driving. Therefore, it could be expected that driving may be more hardly replaced by e-shopping in cities outside Asia because of higher levels of car dependence.

It is also worth noting that the finding in the present study that car owners have a lower likelihood to replace shopping trips with online purchases is not consistent with previous studies (e.g., Weltevreden & Rietbergen, 2007; Xi et al., 2020a). The inconsistent outcomes may be attributed not only to the variation in statistical approaches among these studies, but also to local contexts. In Chengdu (one of the large Chinese cities), public transit is most used for shopping travel for non-car owners. However, a high population density in the city often makes transit users feel overcrowding in vehicles, which imposes additional difficulties in transporting goods by public transit. When e-shopping is an available option, non-car owners may be more likely to replace shopping trips with online buying. This may be another reason why car owners are less likely to reduce shopping trips due to e-shopping than are non-car owners. Therefore, the applicability of the findings in the present study should be reconsidered when informing policy makers in other contexts. In future research, additional empirical evidence from other cities would be useful to examine the generalization of the findings in the present study.

Although this paper contributes new insights to the existing literature, it contains some limitations, thus pointing out several avenues for future research. First, empirical research with true longitudinal designs is still needed in the future. In the present study, a quasi-longitudinal design and a quasi-experimental design are used to capture the effects of e-shopping on shopping trips and the effects of car ownership on changes in shopping trips caused by online buying, respectively. Despite high effectiveness for causality inference, they are not the most ideal designs (Mokhtarian & Cao, 2008; Park et al., 2020). It is widely accepted that a true longitudinal design is most effective to robustly indicate causality (Mokhtarian & Cao, 2008).

Second, the measurement of e-shopping impacts on shopping trips can be extended in two aspects. As indicated in previous studies, e-shopping may have four types of effects on shopping trips, including substitution, complementarity, modification, and neutrality. The present study provides empirical support for the substitution effect, which largely denies the complementary and neutrality effects. However, it is still unknown whether and how e-shopping modifies shopping travel (i.e., the modification effect) according to our analyses. Therefore, in the future, researchers can focus on the modification influence of e-shopping on shopping travel and the role of car ownership. Furthermore, some existing studies indicate that the effects of e-shopping on shopping travel may differ by types of goods (e.g., Zhen et al., 2016). However, the present study does not distinguish the types of goods. More importantly, the car dependence of shopping travel may differ by various types of goods. Therefore, future research can investigate the role of car ownership in the implications of e-shopping for shopping travel by distinguishing types of products.

Third, future research can benefit from optimizing the measurement of household car ownership. In the present study, the impacts of e-shopping on shopping trips are measured by changes in shopping trip frequency after online buying. Ideally, the status of household car ownership when respondents started to shop online should be employed as an explanatory variable. Due to the lack of data availability, however, the status of car ownership when the survey was performed in 2016 is used in this study. Because of this limitation, some respondents who did not own a car when starting to shop online may be treated as car owners in the PSM analyses. Consequently, the negative effects of car owners on the reduction in shopping trips caused by online buying may be underestimated to some extent. This issue needs to be addressed in future research. In addition, we assume that a household owning a car can provide household members with more shopping travel convenience, such as more flexibility of shopping travel and more ease of transporting goods. Therefore, they have a lower likelihood to consider online buying as a substitute for shopping trips. It should be noted, however, that the convenience of shopping travel is not only determined by whether a household owns cars, but also influenced by the number of cars that the household owns, the pro-car attitude, whether a respondent has a driver’s license, and whether car owners choose their cars as the primary travel mode for shopping (i.e., mode choices). These factors should be considered in future research analyzing the association between car ownership and the effects of e-shopping on shopping travel.

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Appendix A: Balance check when considering city-level built environment

Variables	After 1.2 matching				After 1:3 matching				After 1:4 matching			
	Mean		p	S.D.	Mean		p	S.D.	Mean		p	S.D.
	TG	CG	(Diff.)		TG	CG	(Diff.)		TG	CG	(Diff.)	
Sociodemographics												
Gender (Female=ref.)	0.52	0.50	0.715	3.0	0.52	0.50	0.655	3.6	0.52	0.50	0.705	3.1
Age	2.36	2.27	0.266	8.9	2.36	2.27	0.267	8.9	2.36	2.26	0.239	9.4
Education	2.58	2.54	0.590	4.4	2.58	2.51	0.304	8.5	2.58	2.51	0.320	8.2
Income	2.25	2.16	0.242	9.5	2.25	2.16	0.242	9.5	2.25	2.16	0.225	9.9
Living cost	2.50	2.48	0.696	3.1	2.50	2.49	0.858	1.4	2.50	2.48	0.701	3.1
Internet experiences												
Years of using internet on PCs	2.28	2.28	1.000	0.0	2.28	2.27	0.865	1.4	2.28	2.29	0.936	-0.6
E-shopping frequency	8.77	8.61	0.809	2.0	8.77	8.56	0.758	2.5	8.77	8.61	0.809	2.0
E-shopping attitudes												
Satisfaction	-0.02	0.02	0.517	-5.2	-0.02	0.02	0.512	-5.3	-0.02	0.02	0.560	-4.7
Convenience	0.00	0.04	0.567	-4.6	0.00	0.04	0.559	-4.7	0.00	0.03	0.662	-3.5
Low prices	0.01	0.04	0.656	-3.6	0.01	0.03	0.714	-2.9	0.01	0.03	0.762	-2.4
Built environment elements												
Urban areas (Suburban areas=ref.)	0.51	0.48	0.516	5.3	0.51	0.49	0.598	4.3	0.51	0.48	0.588	4.4

Note: TG = Treatment group, CG = Control group; p values are computed by t-test; S.D.=Standardized differences.

Appendix B: Balance check when considering neighborhood-level built environment

Variables	After 1.2 matching				After 1:3 matching				After 1:4 matching			
	Mean		p	S.D.	Mean		p	S.D.	Mean		p	S.D.
	TG	CG	(Diff.)		TG	CG	(Diff.)		TG	CG	(Diff.)	
Sociodemographics												
Gender (Female=ref.)	0.52	0.47	0.230	9.6	0.52	0.47	0.280	8.7	0.52	0.47	0.262	9.0
Age	2.32	2.24	0.370	7.1	2.32	2.25	0.418	6.3	2.32	2.24	0.378	6.9
Education	2.55	2.48	0.339	7.7	2.55	2.48	0.342	7.7	2.55	2.49	0.404	6.7
Income	2.20	2.20	0.983	-0.2	2.20	2.21	0.820	-1.9	2.20	2.21	0.881	-1.2
Living cost	2.49	2.52	0.643	-3.8	2.49	2.52	0.573	-4.5	2.49	2.52	0.578	-4.5
Internet experiences												
Years of using internet on PCs	2.30	2.28	0.742	2.6	2.30	2.30	0.960	0.4	2.30	2.29	0.928	0.7
E-shopping frequency	8.79	8.51	0.688	3.3	8.79	8.53	0.714	3.0	8.79	8.53	0.7.7	3.1
E-shopping attitudes												
Satisfaction	0.00	0.04	0.580	-4.3	0.00	0.07	0.325	-7.6	0.00	0.08	0.283	-8.3
Convenience	0.02	0.02	0.930	-0.7	0.02	0.05	0.574	-4.4	0.02	0.05	0.591	-4.2
Low prices	0.01	0.00	0.953	0.5	0.01	0.03	0.785	-2.2	0.01	0.03	0.759	-2.4
Built environment elements												
Accessibility to bus stations	13.22	12.97	0.684	3.2	13.24	12.82	0.536	4.9	13.24	12.87	0.585	4.3
Accessibility to supermarkets	35.56	34.27	0.430	6.2	35.56	34.14	0.382	6.8	35.56	34.15	0.386	6.8

Note: TG = Treatment group, CG = Control group; p values are computed by t-test; S.D.=Standardized differences.