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**Title:** Do Shared E-Bikes Reduce Urban Carbon Emissions?

**Authors:** Qiumeng Li, Franz Fuerst and Davide Luca

**Affiliation:** <sup>1</sup>University of Cambridge, Department of Land Economy

**Contact corresponding author:** Franz Fuerst: [ff274@cam.ac.uk](mailto:ff274@cam.ac.uk)

# Do Shared E-Bikes Reduce Urban Carbon Emissions?

## Abstract

*Under the threat of climate change, many global cities nowadays are promoting shared commuting modes to reduce greenhouse gas emissions. Shared electric bikes (e-bikes) are emerging modes that compete with bikes, cars, or public transit. However, there is a lack of empirical evidence for the net effect of shared e-bikes on carbon emissions, as shared e-bikes can substitute for both higher carbon emissions modes and cleaner commuting modes. Using a large collection of spatio-temporal trajectory data of shared e-bike trips in two provincial cities (Chengdu and Kunming) in China, this study develops a travel mode substitution model to identify the changes in travel modes due to the introduction of shared e-bike systems and to quantify the corresponding impact on net carbon emissions. We find that, on average, shared e-bikes decrease carbon emissions by 80–150 grams per trip. More interestingly, the reduction effect is much stronger in underdeveloped non-central areas with lower density, less diversified land use, lower accessibility, and lower economic level. Although the actual carbon reduction benefits of shared e-bike schemes are far from clear, this study bears important policy implications for exploring this emerging micro-mobility mode to achieve carbon reduction impacts.*

**Keywords:** Micro-mobility, sharing economy, e-bikes, substitution effects, carbon emissions, land use

# 1. Introduction

Significant carbon emissions have long been a challenge for cities due to the high dependence of transportation on fossil fuels and a car-dependent lifestyle (Sloman and Hopkinson, 2020). Many global cities have introduced a variety of policies to promote sustainable transportation to reduce carbon emissions in cities and combat the challenges of climate change. Reducing carbon emissions in urban transport is particularly important for cities in developing countries. By 2050, two-thirds of the world population will live in urban areas, while about 95 percent of urban expansion in the coming decades will take place in developing countries (United Nations, 2019). China is the largest developing country undergoing rapid urbanisation. As more and more people move to cities in China, the challenges of urban congestion and emissions pollution will become even more acute.

One of the major developments in green and shared urban transportation in recent years is shared electric bikes (e-bikes) sharing systems, a novel type of micro-mobility service. Developed based on bike-sharing, an earlier form of shared micro-mobility service, e-bike sharing has gradually become the focus of governments and companies (Kr-asia, 2020), as it is accessible on an “as-needed” basis and can offer travel at higher speeds with less physical effort than shared bikes, i.e. exclusively human-powered bicycles which we will refer to simply as bikes throughout this article. With considerable capital

investments being poured into their development, shared e-bikes continue to land in new cities and the market is growing exponentially (Elliott Ramos, 2021).

However, whether shared e-bikes can help to achieve carbon reduction in cities is yet under debate. Shared e-bikes can either replace the unsustainable commuting modes that rely on fossil energy (e.g., by car) or substitute for some even cleaner commuting modes (e.g., by bike). Compared to cars or public transit, shared e-bike trips are more flexible and solve last-mile connectivity problems. Meanwhile, some citizens may be attracted to shared e-bikes because it is easier to travel longer and overcome road barriers than by using bikes (P Rérat, 2021). Since e-bikes are greener than cars but have greater carbon emissions than bikes, the net substitution effect of shared e-bikes on carbon emissions is ambiguous, since it depends on the forms of transportation combinations they substitute.

A few past studies have used either simulations or surveys to investigate this research question (Bucher et al., 2019; McQueen et al., 2020; Wamburu et al., 2021), but there is still a lack of direct empirical evidence. In addition, existing studies have discussed the impact of various factors (e.g., weather and temperature) on the adoption of shared e-bikes (Bucher et al., 2019), while a few studies have explored the impact of the built environment (e.g., land use and accessibility) on the net carbon emissions of shared e-bikes. Specifically, the substitutional choices between alternative transportation modes

are expected to vary in different urban contexts, which will result in spatial heterogeneities in the associated carbon emissions reductions. For example, in more compact and accessible neighbourhoods, people are expected to prefer walking or cycling, so e-bikes are more likely to substitute for green transport modes than cars in those areas. In which urban built environments will the development of e-bike sharing be more effective in reducing carbon emissions has not been explored.

To bridge these two knowledge gaps in the literature, we use China, one of the largest e-bike sharing markets in the world, as the case study. Using complete daily trip-level shared e-bike data from one of the largest shared micro-mobility companies in two provincial cities (Chengdu and Kunming) in China, this study investigates the net effect of adopting shared e-bikes on urban carbon emissions, after considering their substitutions for alternative commuting modes. We first present a travel mode substitution model to identify the changes in commuting modes due to the introduction of shared e-bike services and quantify the corresponding changes in carbon emissions per trip. Then we analyse the correlations between these changes in carbon emissions and the urban features, to reveal what kind of places contribute to the carbon reduction effect of shared e-bikes. We find that, on average, shared e-bikes result in a decrease in carbon emissions by 80–150 grams per trip, compared to the substituted modes. Assuming 0.18 million e-bike trips in a city per day, this amounts to a reduction in carbon emissions by 14–27 tonnes. More importantly, the reduction effect is much

stronger in underdeveloped non-central areas with lower building density, less diverse land use, and lower accessibility, potentially because shared e-bikes in these regions are more likely to replace transport modes that rely on fossil energy. This study provides advice for government and businesses to deploy shared e-bikes and to improve the cycling infrastructure in suitable locations.

## **2. Literature review**

Transportation is acknowledged as one of the most important contributors to greenhouse gas emissions, accounting for nearly a quarter of total emissions and rising annually (IPCC, 2014; IEA,2020). Due to the high carbon emissions from the unsustainable transport modes that rely on fossil energy, green changes in people's travel behaviour may have a positive environmental impact on sustainable cities. The booming of shared micro-mobility is regarded as a potential contributor to the behaviour change of car-dependent lifestyles and carbon reduction (Cao & Shen, 2019; Cerutti et al., 2019; Jones et al., 2016; McQueen et al., 2019). Bike sharing, as an earlier form of shared micro-mobility system, has developed for more than half a century(Wang & Sun, 2022). From the first bike sharing system in Amsterdam(DeMaio, 2009; Ploeger & Oldenziel, 2020) to the emergence of e-bike sharing on the streets around the world (Galatoulas et al., 2020), the development of shared micro-mobility has made it more convenient for human mobility and activities.

Shared e-bikes combine the merits of shared bikes and electric vehicles and present the potential to change travel behaviour (Winslott Hiselius & Svensson, 2017). Compared to bikes, e-bikes can travel higher speeds with less physical effort (Cherry, 2007; Popovich et al., 2014), travel for longer distances, and climb slopes easily (Allemann & Raubal, 2015; Dill & Rose, 2012). Unlike conventional bikes which mainly aim to resolve the last-mile connectivity problem only, e-bike sharing trips also have the potential to become an alternative to short- and medium-distance car trips (Haustein and Moller, 2016; Moser et al., 2018; Ioakimidis et al., 2016). Compared to car trips, an e-bike sharing trip is cheaper, takes up less space, is less affected by traffic congestion (Wamburu et al., 2021), and has a higher energy efficiency level (Berners-Lee, 2021; Weiss et al., 2015). In China, the price of riding a shared e-bike is as low as using public transit, costing only CNY 2 (GBP 0.228) per half hour. Studies in several Chinese cities have suggested that e-bikes can be an affordable alternative to public transit (Cherry & Cervero, 2007; Montgomery, 2010; Cherry et al., 2016). As a shared mobility method, people can use shared e-bikes in the short term according to their spontaneous travel needs (Machado, et al., 2018; Shaheen, et al., 2015). It is estimated that there will be 8 million shared e-bikes in China by 2025 (Aurora Mobile, 2021).

## **2.1 Estimating the carbon reduction potential**

The popularity of e-bike sharing has also triggered discussions on its role in the sustainable development of cities, especially in carbon emission reduction. Most studies

have explored the environmental benefit of bike sharing (D’Almeida et al., 2021; Fishman et al., 2014; Kou et al., 2020; Wang & Sun, 2022). However, for e-bike sharing, knowledge about the environmental impact of this emerging micro-mobility mode is scarce. Although for-profit companies assert that e-bike sharing can reduce carbon emissions (Hellobike, 2021), scholars have not reached a consensus that shared e-bikes have an environmental benefit. Whether developing e-bike sharing services has a net positive effect on reducing carbon emissions depends on what modes of transportation they have substituted for. Based on a meta-analysis of published articles from China, Europe, North America, and Australia, Bigazzi & Wong (2020) reported that the highest proportion of alternative transport modes replaced by e-bikes is public transit (33%), followed by bikes (27%), cars (24%) and walking (10%), and this result varies across different countries. The carbon emissions of e-bikes are higher than conventional bikes, slightly lower than public transit, and much lower than cars (McQueen et al., 2020). Therefore, to quantify the net impact of e-bike sharing on carbon emissions, the first step is to understand what transportation modes are more likely to be replaced by shared e-bikes.

Some studies stated that e-bikes, as a promising carbon-efficient alternative to cars, have the potential to reduce carbon emissions by changing unsustainable travel habits (Haustein & Moller 2016; Winslott Hiselius & Svensson 2017; Harvey & Guo, 2018; Moser et al., 2018). It has been found that car trips are the main mode replaced by e-



bikes in North America and Australia (MacArthur et al., 2014, 2018; Johnson & Rose, 2013). McQueen et al. (2020) stated that e-bikes reduced the share of car trips in all journeys by about 10 percentage points and lowered carbon emissions by 225 kg per year in North America. Some researchers estimated the car kilometers substituted by e-bikes amongst surveyed users (Cairns et al., 2017; Moser et al., 2018). Bucher et al. (2019) simulated the reduction in greenhouse gas emissions by e-bikes under different transportation and weather scenarios, based on car trip information. The study found that the reduction of emissions could reach up to about 10% of the overall greenhouse gas emissions in Switzerland. In the summarised study of Berjisian & Bigazzi (2019), the net carbon reduction per e-bike in use was estimated at around 460 kg p.a,

However, some studies have challenged the green mode shift effect of e-bike trips. In the Netherlands e-bikes have only significantly reduced conventional bicycle trips, and not the other transport modes like cars, thereby bringing adverse effects (De Haas et al., 2022); Jones et al., 2016). Bieliński et al. (2021) pointed out that shared e-bikes have a significant substitution effect for public transport instead of car trips in Tricity, Poland. Sun et al. (2020) found that e-bikes substitute more conventional bike use than car use in Netherland, but they still have a net gain in environmental sustainability, because the share of bike kilometers is significantly smaller than that of cars.

So far, the empirical findings about the environmental potential of shared e-bikes are

mixed in different urban contexts. Existing studies have mainly used simulations and surveys to explore the behaviour change and environmental potential of shared e-bikes. The most common method is the intercept survey-based method (Cairns et al., 2017; Cherry et al., 2016; Fyhri et al., 2017; Lin et al., 2017; Mcqueen et al. 2020; Moser et al., 2018). The arguments are based on a similar question: “If the target mode (e.g., shared bike or e-bike) was unavailable, what kind of transportation would you choose?” The findings of these surveys show diverse results of the substitution effects, which vary according to their different questionnaire design, sampling rules, and local contexts. Due to limitations of questionnaire sample size on the analysis of individual systems, samples could not be fully representative of the overall users (Fukushige et al., 2021; Kou et al., 2020), which may cause bias and validity problems for the analysis of net carbon emissions changes attributable to shared e-bikes.

## **2.2 Conditions for shared e-bikes to be successful**

The relationship between environmental potential and shared e-bikes depends on people’s travel substitution choices, so the factors affecting the travel choice are worth to be identified in another line of research. Land use is the most crucial factor in travel choice. In the early research, Cervero & Kockelman (1997) proposed the ‘3D’ elements – density, diversity, and design – and demonstrated that high-density, diverse land uses and road network design helped to reduce the commute frequency, as well as reduce car travel, and thus reduce carbon emissions. Furthermore, Cervero (2002) put forward the

'5D' elements – density, diversity, design, distance to transit, and destination accessibility. Ewing & Cervero (2010) added another two 'Ds', demand management and demographics, to compose a '7D' concept, but this is less related to the attribute of land use. Density is the essential variable. Boarnet et al. (2008) found that in a higher density region, citizens prefer to walk, especially in a high-density retail area, contributing to carbon reduction. Moilanen (2010) found that employment density was proportional to non-car transport choices. Diversity is another important factor. Peng (1997) indicated that the job-housing rate had a U-shaped relationship with car travel distance per capita, meaning that the job-housing balance could reduce car usage and bring environmental benefits. Frank et al., (2008) also found that road connectivity and land use mixed degree promoted the probability of walking.

As for the factor influencing bike sharing behaviour, although extensive studies have explored the influence of the built environment, weather, environment, and other factors on bike usage (Eren & Uz, 2020; Mattson & Godavarthy, 2017; Nankervis, 1999; Spencer et al., 2013; Winters et al., 2010), but few studies specifically address factors influencing the environmental potential of e-bikes. Fukushige et al. (2021) found that long e-bike sharing trips and trips originating from non-commercial areas have a higher propensity to reduce car use, while trip distances less than 1 mile are more likely to replace walking, according to a survey in Sacramento. Sun et al. (2020) showed that e-bike riders would be more likely to substitute cars in less urbanized areas. From the

disaggregated perspective, what kind of geospatial context in which the future placement of e-bikes will enhance their environmental benefits is still unclear.

### 3. Research Strategy

Ascertaining the carbon emissions reduction potential of shared e-bikes involves the construction of a valid counterfactual. In other words, if there were no shared e-bike available for a trip, what alternative mode would a traveller choose? Fig. 1 illustrates the stepwise procedure of our empirical analysis. Firstly, according to the key indicators mentioned in previous studies, such as distance, time, and transit coverage of a trip, a travel mode substitution model is established to simplify the complex problem of substitution and to make it measurable. Four potential substituted modes (driving, public transit, walking and cycling) are included in our analysis.

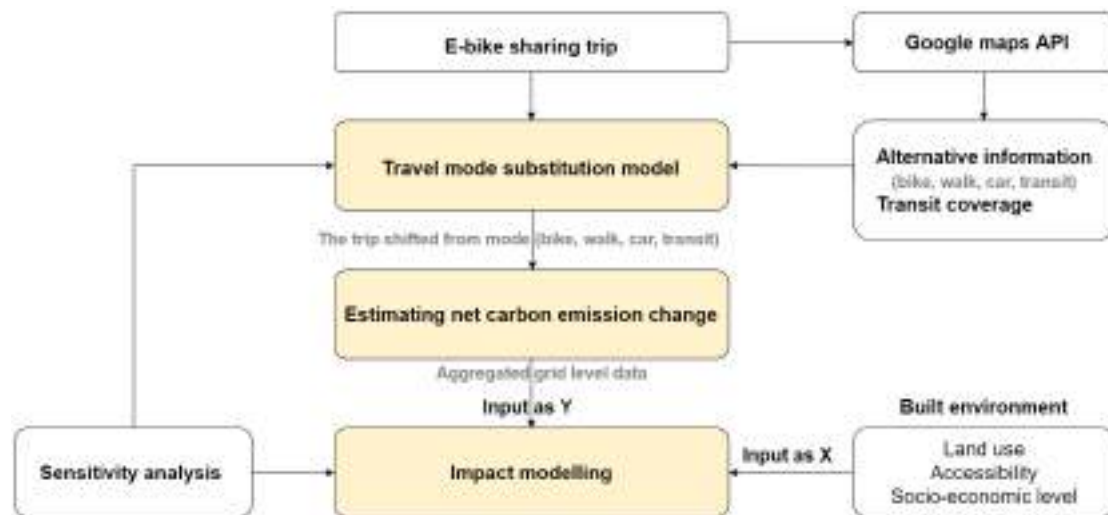


Fig. 1. Carbon emissions modelling steps for shared e-bikes.

The distance and duration of route of each trip can be crawled using the Google map developer platform API by inputting the time, origin, and destination (OD) coordinates of each e-bike sharing trip (Fig. 2). In terms of the information available on potential substituted transportation modes, we crawled the duration and distance of alternative modes for the same OD locations via Google Maps API, and retrieved information about whether the OD locations lie within the coverage of public transit. The above information can be used in the travel mode substitution model to measure which mode is more likely to be replaced by a given shared e-bike trip, and to hence estimate the net carbon emissions change. The net carbon emissions reduction effect of e-bike sharing in a place depends on the different substituted combinations. How much net carbon emissions are reduced or increased by shared e-bikes substituting for other transportation modes can be calculated by multiplying by the carbon emissions coefficient of each substituted mode. The change in net carbon emissions of each trip with its origin in the grid are aggregated to the same grid. Finally, impact analysis models are built to unpack the urban features that influence the carbon emissions reduction effect of shared e-bikes. The net carbon emissions per trip in each grid are put into the models as the Y variable. Land-use variables of each grid, like density and diversity, are put into the models as X variables.



Fig. 2. The process of crawling potential substituted mode information from the Google Map developers API. (The base map is from Google map)

### 3.1 Travel mode substitution model

This section estimates the substitution of individual e-bike trips for other modes based on the distance, time, and transit coverage of the trip. The method is designed to identify the mode of transportation with the highest probability of being replaced or complemented by a shared e-bike trip (Fig. 3).

Firstly, trip distance is a determining factor for measuring the choice of different travel modes (Fig. 4) (De Sá et al., 2015; Ermagun & Samimi, 2018; Fitch et al., 2021; Kim et al., 2020; Kong et al., 2020; Lee et al., 2021). For example, if a trip taken by e-bike has a significantly long distance, the motivation to replace a bike trip with an e-bike ride will be lower than replace a car trip. For the relationship between non-motorised travel and motorised travel, Zhang and Mi (2018) set a threshold (e.g., 1 km) for the trip distance: if the distance is less than the threshold, people prefer to choose walking or cycling as an alternative; if above the threshold, people are inclined to choose a

motorised trip, because for long trips, travellers would have taken a taxi or private car. This paper sets the first threshold ( $D_{t1}$ ) based on the relationship between the distance and frequency of various transportation means in the empirical data. (In the robustness section, we will also test the sensitivity of results to alternative thresholds.) For trips with a travel distance ( $D$ ) lower than the first threshold ( $D_{t1}$ ), we assume that people will be more likely to choose non-motorised modes, such as walking or cycling. This paper sets 500 m as the threshold ( $D_{t2}$ ) of a comfortable walking distance (Gehl and Koch, 2011; Li et al., 2019) to distinguish walking and cycling. Most walkers feel tired when they walk further than 500m (Gehl and Koch, 2011).

For trip distances ( $D$ ) above the first threshold ( $D_{t1}$ ), people are more likely to choose motorised modes, such as cars or public transit. The accessibility of public transit is a critical aspect affecting people's choices (Liao, 2021). This paper combines the method of the substitution relationship between public transit and cars in Kong et al. (2020), using transit coverage of the trip to distinguish between public transit and driving. The transit coverage analysis includes two steps: spatial coverage and temporal coverage. In transit spatial coverage analysis, if both the trip origin and destination (OD) are within the buffer of transit stops, then the areas are considered to be accessible for a transit trip. Previous studies have usually set the buffer to 400 m, as the comfortable distance for people to walk to transit stops (Demetsky and Bin-Mau Lin, 1982; Hawas et al., 2016). If the conditions for spatial coverage are met, we consider the temporal

coverage. Different transit stops have different operation times. If users have to wait for a long time, they may not choose transit for the trip. The paper set 30 minutes as the travel time difference threshold ( $T_t$ ) of public transit and car trips, in line with the time difference parameter measured in Kong et al. (2020). If there is no transit available within a given spatial buffer and temporal coverage, people will choose to use the car, otherwise, they will choose public transit. Besides spatial and temporal coverage, the service quality of public transit also affects people's choices. Many aspects determine service quality, such as safety, crowdedness, privacy, etc. It is important to note that data on service quality is not available, hence our study does not take this unobserved factor into account, at least not explicitly.

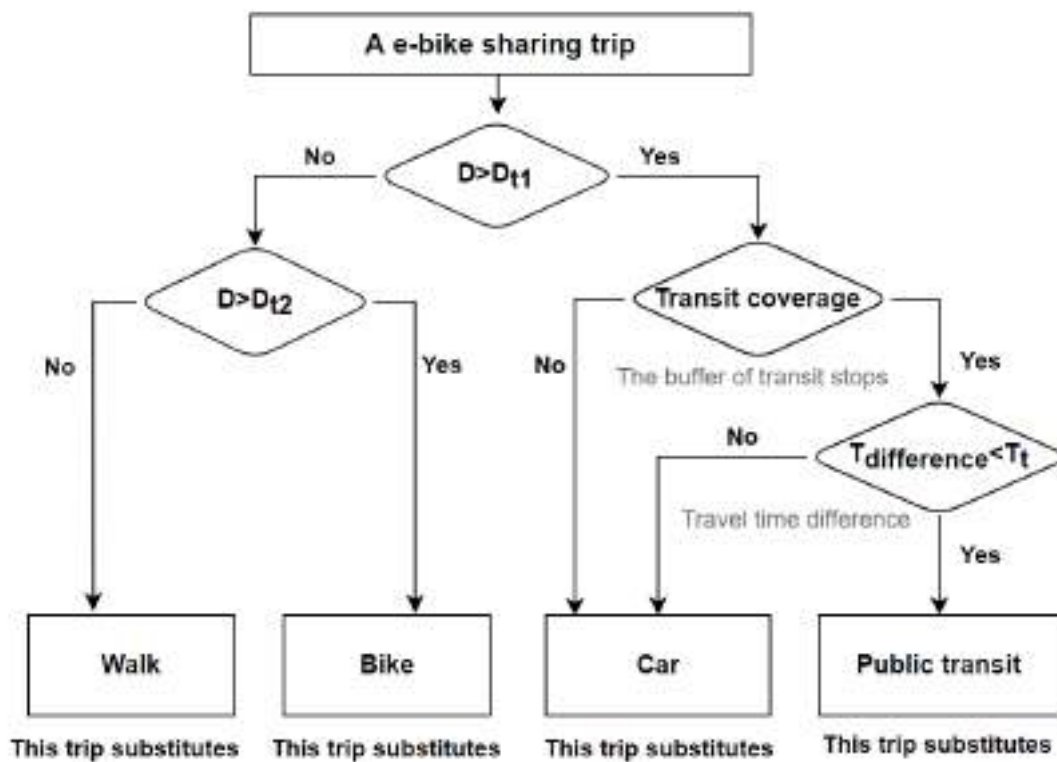


Fig. 3. Travel mode substitution model



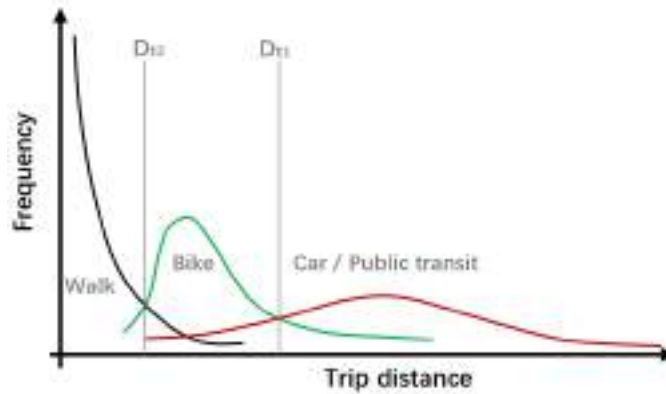


Fig. 4. The conceptual relationship between travel distance and frequency of different travel modes

### 3.2 Carbon emissions analysis

To analyse net carbon emissions changes, we develop a comprehensive measure of different substitution combinations. Taking the carbon analysis of a 100\*100m grid sample as an example (Fig. 5), and assuming that 10 e-bikes launch their trips from that specific origin (the white grid), the paper will first use the method described in section 3.1 to infer which transport mode has been replaced by each e-bike trip. We will then take the carbon emissions parameters (Table 1) of the substituted transport mode and multiply it by the distance by the corresponding mode crawled from the map API. Finally, we will subtract the carbon emissions generated by shared e-bikes from the carbon emissions generated by the replaced original mode trips to obtain the change in net carbon emissions. The specific formula designed in the paper is as follows:

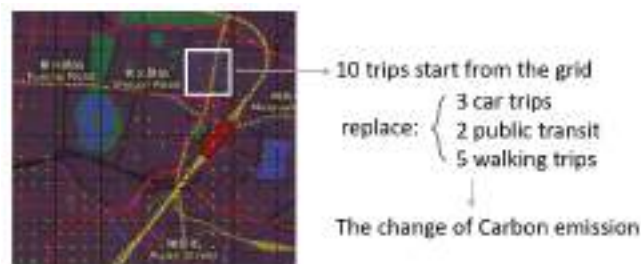


Fig. 5. A grid sample for measuring the net carbon emission

$$E_i = (E_{drive} \sum_{d=1}^a D_d + E_{transit} \sum_{e=1}^b D_t + E_{active} \sum_{f=1}^c D_f) - E_{ebike} \sum_{j=1}^n D_j \quad (1)$$

$$E_{drive} = p \cdot \rho \quad (2)$$

where  $E_i$  represents the total carbon emissions reduction of shared e-bikes in spatial grid  $i$ ,  $n$  is the number of e-bike sharing trips originating in grid area  $i$ ,  $a$  is the number of substituted car trips,  $b$  is the number of substituted public transit trips, and  $c$  is the number of substituted active mode trips (walking or cycling). If  $E_i$  is greater than zero, it means that shared e-bikes starting within this grid, decrease the carbon emissions and have a positive impact on the environment. If  $E_i$  is almost equal to zero, it means that shared e-bikes have no environmental benefit. If  $E_i$  is less than zero, it means shared that e-bikes have a negative effect on the environment. For trips with the same origins and destinations, the distances travelled by cars, buses and bikes may not be the same.

Table 1. Carbon emission parameter.

Mode	Carbon emission parameter	Value	Unit	Reference
Car	$E_{drive}$	223.9	g CO <sub>2</sub> /P·km	(Zhang & Mi, 2018)
Public Transit	$E_{transit}$	26.0	g CO <sub>2</sub> /P·km	(Yang & Zhou, 2020)
E-bike	$E_{ebike}$	4.9	g CO <sub>2</sub> /mile	(McQueen et al.2020)
Walking/bike	$E_{active}$	0	g CO <sub>2</sub> /P·km	(Mcqueen et al., 2020) (Zhang & Mi, 2018)

When calculating carbon emissions, the travel distance of each transport mode is based

on the real route distance crawled by Google API, rather than the straight-line Euclidean distance of OD points, to improve the accuracy of the calculation. The definitions of other variables are as below:

$E_{drive}$  : per kilometre carbon emissions parameter of a car trip (g CO<sub>2</sub>/P·km )

$E_{transit}$  : per kilometre carbon emissions parameter of public transit (g CO<sub>2</sub>/P·km)

$E_{active}$  : per kilometre carbon emissions parameter of walking or cycling (g CO<sub>2</sub>/P·km)

$E_{ebike}$  : per kilometre carbon emissions of a shared e-bike trip (g CO<sub>2</sub>/P·km)

$D_j$  : distance of trip j by a shared e-bike (km)

$D_d$  : distance of trip d by driving (km)

$D_t$  : distance of trip t by public transit (km)

$D_f$  : distance of trip f by walking/cycling (km)

p : Petrol consumption per unit of distance travelled (L/km)

$\rho$  : The density of petrol (kg/L)

### **3.3 Modelling the impact of carbon emission changes**

To explore the interaction between urban structure and the carbon reduction effect of shared e-bikes, this paper takes land use, accessibility, and socio-economic factors into account, based on land use-transport interaction theories (Wegener and Fuerst. 1999).

We develop an empirical regression model where the dependent variable is the average net carbon emissions of all trips originating from each 100\*100 m grid. We regress such measure on the independent and control variables listed in Table 2. We first use a simple ordinary least squares estimator (OLS), and then a more complex Spatial Durbin Model (SD) to avoid errors caused by spatial interdependence between carbon emissions reduction effect of shared e-bikes and the spatial lags of both the outcome and urban features. The spatial lag regression formula is listed as follows:

$$y_i = \log\left(\frac{E_i}{N_i}\right) \quad (3)$$

$$y_i = \lambda w_i y + x_i \beta + w_i X \theta + \varepsilon_i \quad (4)$$

where  $y_i$  represents the net carbon emissions per trip in spatial unit  $i$  in log form, and  $N_i$  is the total number of e-bike sharing trips in grid area  $i$ . When  $y_i$  is above zero, this means that the shared e-bikes reduce the carbon emissions in unit  $i$ ; otherwise, the net carbon emission in unit  $i$  increases.  $w_i$  is the spatial weights vector, and the neighbourhoods are based on the rule of Queen's case.  $\lambda$  is the spatial lag coefficient of  $y$ , and  $\theta$  is the vector of coefficient of  $x_i$ .  $x_i$  is the collection of independent variable  $j$ , including land use characteristic, accessibility and economic activity level, and control variables, including population density, average trip duration and the utilization efficiency of shared e-bikes, which is calculated as the count of trips divided by the count of shared e-bikes in grid  $i$ .  $X$  is the matrix of explanatory variables and  $\theta$  is a

vector of parameters.  $\varepsilon$  indicates the unobserved error.

It is well documented in the extant literature that the built environment shapes travel behaviours and vice versa (Ewing & Cervero, 2010). In this paper, four measures are used to describe the built environment: land use diversity, land use intensity, road density, and the number of public transit stations and stops. Land use intensity is measured by the floor area ratio (FAR). The road density index is represented by the reciprocal of block size. For the socio-economic aspect, this paper uses the night light index as a proxy of the economic activity level of areas. When an area has a high night light index, this generally indicates there are a lot of commercial activities, relatively high economic income, and development. Many studies have found a closer connection between light and economic activity (Mellander et al., 2015). The land diversity level is calculated by the degree to which there is a mixture of diverse POI types. Generally, the diversity level can be presented by the Shannon entropy index (Shannon, 1948), which can be formulated follows:

$$D = - \sum_j^c h_j \log_n h_j, \quad (5)$$

where  $D$  is the entropy index, which range from 0 to 1.  $h_j$  is the proportion of the  $j^{\text{th}}$  type of normalized POI, and  $n$  is the number of categories. A value of 1 represents extreme diversity of land function, whereas a value of 0 indicates there is only one type

of POIs in specific unit.

Table 2 Descriptive statistics.

		Mean	Std dev	Min	Max
<b>Dependent variables</b>					
	The net carbon emissions reduction per trip in each grid	165.87	264.72	-4.87	3289.25
<b>Independent variables</b>					
Land use characteristic	Land use diversity	0.63	0.29	0	1.10
	Land use intensity	1.46	1.46	0	18.43
Accessibility	Road density index	10.34	18.72	0.04	193.67
	Counts of public transit stations and stops	0.71	1.35	0	6
Economic activities	Nighttime light index	29.04	13.76	3.47	77.02
<b>Control variables</b>					
	Population density (X 10000 per m <sup>2</sup> )	71.16	41.31	0	203.75
	The utilization efficiency of shared e-bikes (Counts of trips /Counts of shared e-bikes)	1.05	0.06	1.00	2.00
	Average trip duration (in minutes)	12.69	4.78	3.19	135.23

## 4. Data and study area

China has the largest number of shared e-bikes in the world. After the dockless shared bike race that took China by storm from 2016 to 2018, many tech companies are now betting on a similar yet different business: e-bikes (Krasia, 2020). Electric bike-sharing systems emerged in 2017 and rose to prominence after 2019. From 2019 to 2022 there has been a rapid development period for shared e-bikes. Due to policy restrictions in most of the big cities in China, shared e-bikes mainly operate in small cities and counties. Kunming and Chengdu are among the few big cities where government policies encourage the use of shared e-bikes. This paper chooses the urban main area of Kunming and three sub-centre districts of Chengdu (Fig. 6) as the study area ( shared e-bike systems were launched in Pidu, Wenjiang and Shuangliu districts, and were not

allowed to launch in the city centre of Chengdu). Kunming has a population of over 5 million people, and the three sub-centre districts of Chengdu have a population of over 2.5 million people.

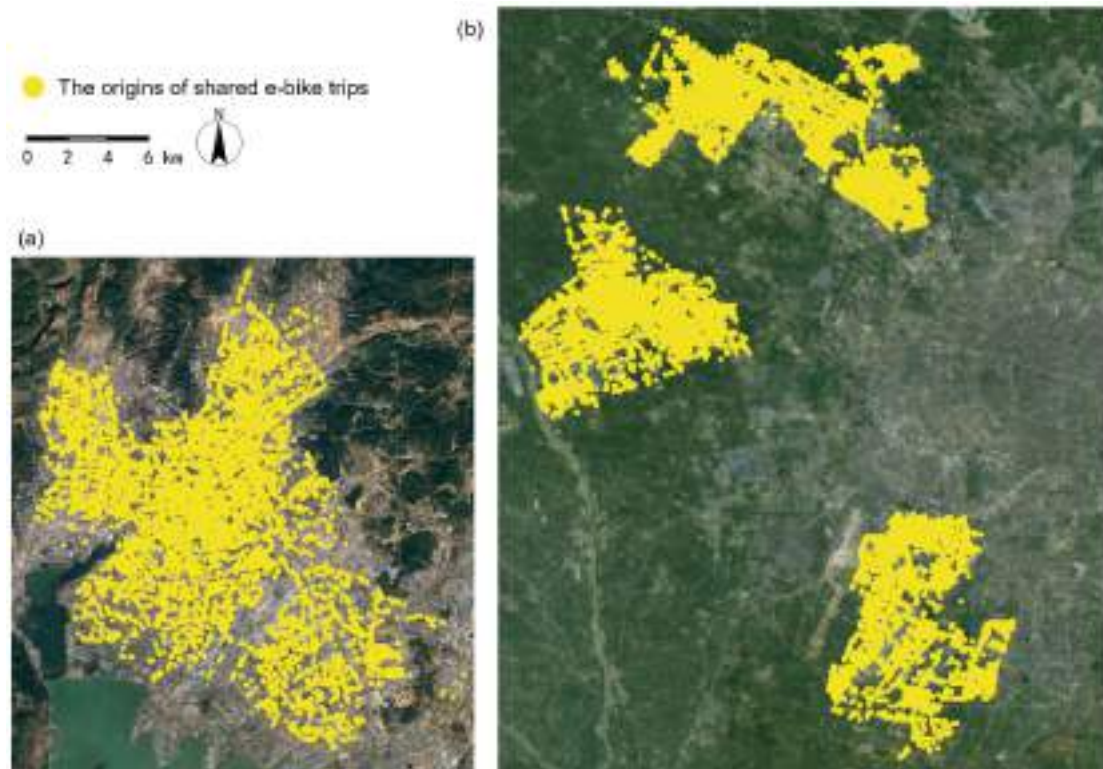


Fig. 6. The study area and spatial distribution of origins of shared e-bike trips in (a) Kunming and (b) Chengdu (The base map is from satellite map of Google and the dataset is from Meituan).

Compared to previous studies based on traditional survey data analysis (Cherry et al., 2016; Lin et al., 2017), this paper analyses the carbon emissions reduction effect of shared e-bikes based on big data analysis. The e-bike sharing trip data is the most important input in this study. Data from 4 million recorded trips are collected in two cities, including user attributes (user id, gender, and age), trip attributes (start and stop time, date, and location) and bike id (Table 3). The time span of the data covers two weeks in March 2021. All users are anonymous so that privacy is protected. Bike-sharing trip data was also collected in 2020 and Taxi trip data in 2018 from Meituan

and DIDI companies, to analyse the difference in distance distributions between cycling and driving, which could give reference for the distance threshold setting in the travel mode substitution model.

Table 3. Example of e-bike sharing trip records.

Order id	City	Date	User id	Bike id	Gender	Age	Register date	Origin (X,Y)	Destination (X,Y)	Start Time	End Time
Trip No. 1	Kunming	2021-03-02	8979	7865	Female	28	2020-08-02	25.02, 102.42	24.32, 102.13	12 : 50	13 : 02

## 5. Results

To explore whether shared e-bikes reduce carbon emissions and in what kind of urban context shared e-bikes are more effective at reducing carbon emissions, we analysed the competition between potential substituted travel modes by shared e-bikes, the spatial patterns of the changes in net carbon emissions attributable to shared e-bikes, and the impacting factors with a view towards choosing the optimal deploying strategy for shared e-bikes to boost reductions in carbon emissions. Hence, our analysis focuses on the impact of the urban features of starting locations on the carbon emissions reduction effect of shared e-bikes.

### 5.1 Mode substitution

Shared e-bike trips with a distance longer than 10 km or a duration longer than 3 h were deleted. After data cleaning, there were 2,463,596 trips in Kunming and 1,322,749 trips in Chengdu. Fig. 7 shows the relationship between the time and distance of using other



travel modes with the same starting and ending points as the e-bike sharing trips, by crawling data from Google API. Based on the travel duration and frequency distribution of transportation modes over different distances, the competition between different travel modes lies mainly in the distance interval from 1 km to 3 km. We use the distance frequency of shared bikes and taxis to represent the distance frequency of bikes and cars (Fig. 8). The average trip distance of shared e-bike trips was 2.24 km, and the travel distance overlaps the trip distance range of bikes and cars. A travel distance of around 1600 m is a critical value. When the distance is less than 1600 m, the probability of people using non-motorised tools such as bikes is higher; when the distance is longer than 1600 m, the probability of people using motorised vehicles such as cars is higher. Therefore, this paper initially set 1600 m as the threshold ( $D_{t1}$ ) in the travel mode substitution model. To make the result more convincing, the following sensitivity analysis has been conducted under different threshold parameters in the travel mode substitution model.

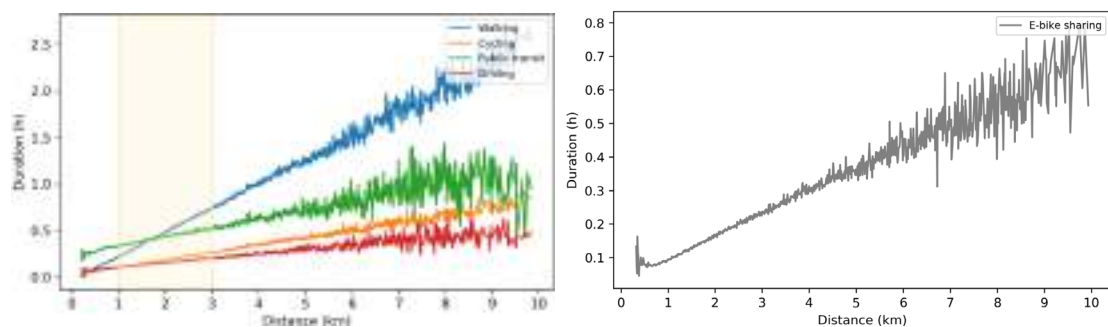


Fig. 7. Travel duration of different transportation means regards to different travel distances (The data is crawled from Google map developer platform API)

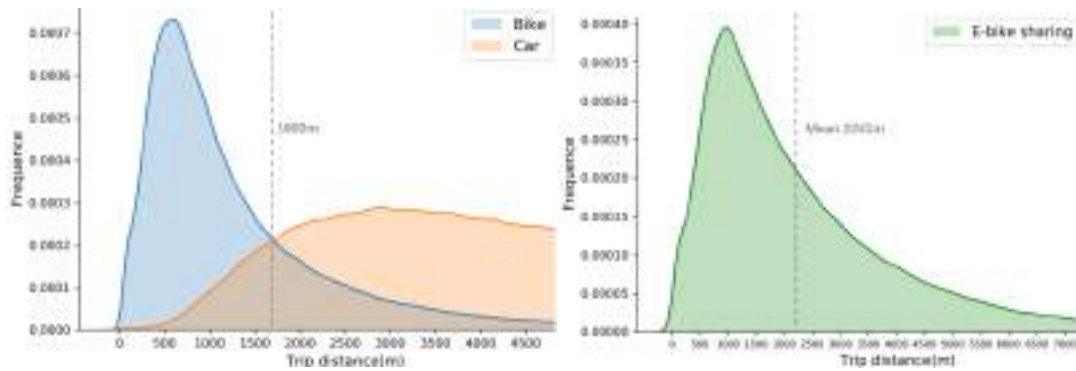


Fig. 8. Travel frequency of bikes, cars and shared e-bikes with regards to different travel distances (The data is from Meituan and DiDi).

## 5.2 Spatial patterns of emission changes

The result from the travel mode substitution model shows that in Kunming 5.5% of e-bike sharing trips replaced walking, 41.0% of the trips replaced bike trips, 43.4% replaced public transits, and 10.1% replaced car trips, while in Chengdu the percentage of shared e-bike trips that replaced walking, bicycles, buses, and cars was 6.1%, 40.6%, 43.3%, and 10.0%, respectively. The proportion of e-bikes substituting for other modes of transportation is similar between the two cities and the average net emissions reduction per trip is 121 g. Although a larger proportion of e-bike sharing trips substitute green modes than high carbon emission vehicles, the net emissions are reduced. This is because the travel distances of shared e-bike trips that replace cars are longer than those of the trips replacing low carbon modes, such as walking or cycling, and shared e-bikes themselves are a low-carbon transportation mode and the carbon emission parameter is small. Therefore, the emissions reduced by replacing one car trip are far greater than the emissions increased by replacing one bike/walking trip.

The net carbon emissions change of Kunming and Chengdu has been measured based on the result of the travel mode substitution model. To better understand the impact of the location of e-bike sharing trips on the net emissions, we analysed the spatial patterns of net emissions changes. We allocated the carbon emissions of each trip to its start point (since the origin of a trip generally reflects the demand for travel and provides the location information of where to deploy the shared e-bikes); the net carbon emissions of these start points were merged into the centre of the 100\*100 m grid and the centre of the 500\*500 m grid to plot the carbon emissions changes by origin centre points on the maps (Fig. 9, Fig. 10).

The carbon emissions reduction effect of shared e-bikes exhibits significant spatial heterogeneity. The spatial pattern of net emissions at the 100\*100 m level is relatively complex and not intuitive, so we also plotted net emissions at the 500\*500 m level. In the map, the higher the net CO<sub>2</sub> emission reduction, the colder the colour, and orange represents the increase in CO<sub>2</sub> emissions attributable to shared e-bikes. It can be observed that e-bike sharing does not decrease carbon emissions everywhere, but increases CO<sub>2</sub> in certain places. In 86% of spatial grids, the launch of shared e-bikes could help to reduce carbon emissions. Shared e-bike trips in non-central areas decreased more emissions than in central areas. The relationship between the typical urban features of shared e-bike placement and net carbon emissions is explored in the following analysis.

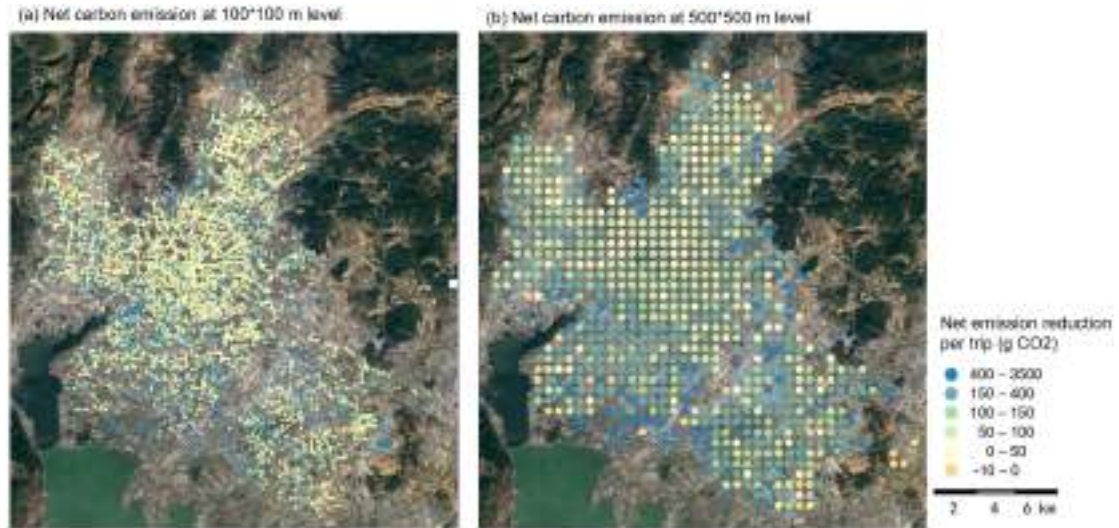


Fig. 9. The spatial distribution of carbon emissions reduction per trip in Kunming (The base map is from satellite map of Google and the data comes from the analysis of the raw e-bike sharing trip records).

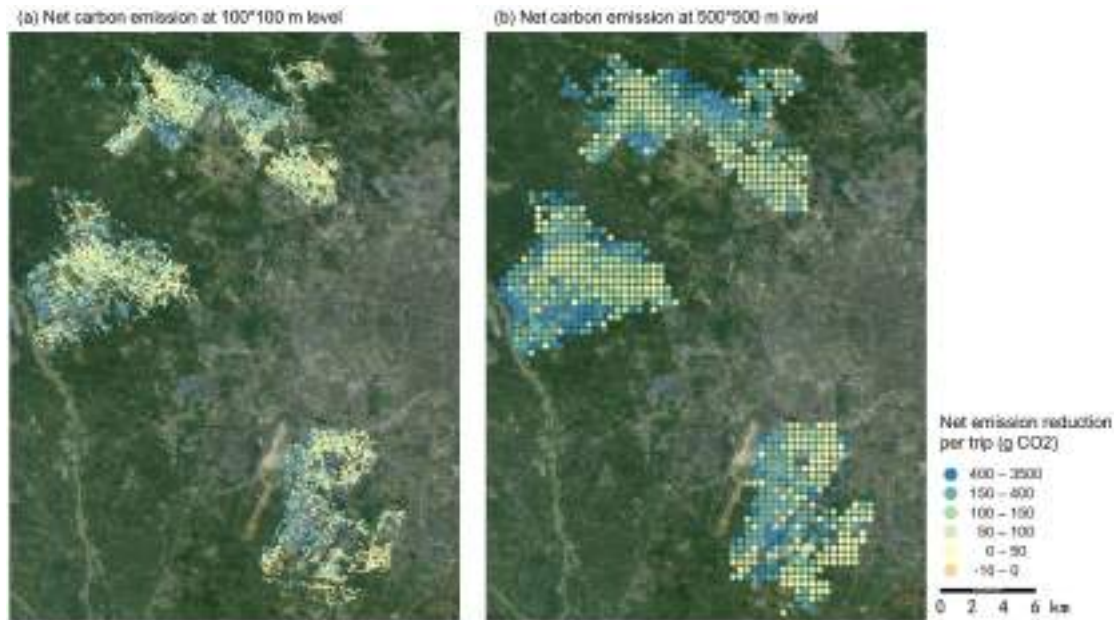


Fig. 10. The spatial distribution of carbon emissions reduction per trip in Chengdu (The base map is from satellite map of Google and the data comes from the analysis of the raw e-bike sharing trip records).

### 5.3 Which built environments are conducive to carbon emission reductions?

To explore the relationship between features of the built environments and reductions in the carbon emissions attributable to shared e-bikes, we regress the impact of land use,

accessibility, and socioeconomic factors on the changes to net carbon emissions attributable to e-bike sharing. Regarding the results of the OLS model, the coefficients of land-use diversity, land-use intensity, road density, public transport stops, and economic activities are all significantly negative in both cities (cf. Table 4). This indicates that places with single land use function, low land-use intensity, low accessibility and low economic level, such as the suburbs of urban areas, could boost the carbon reduction effect of shared e-bike trips. To avoid errors caused by spatial interdependence, the study also uses Spatial Durbin Model to accommodate spatial dependence between carbon emissions reduction effect of shared e-bikes and the spatial lags of both the outcome and urban features. After considering spatial lags of variables, most fixed characteristics become insignificant, while many spatial lags of the explanatory variables are significant, indicating that these characteristics of adjacent areas affect the carbon emissions reduction effect. To be more specific, the spatial lag of land use diversity and public transport stops are significantly negative in both cities. The spatial lag coefficient of the land use intensity, economic activities, and road density are significantly negative in one city case, and insignificant in another one, indicating the dependence between carbon emissions reduction effect and these urban features of adjacent areas is unstable, with certain randomness. Among all variables, land use diversity and public transport facilities are the relatively stable determinants relating to the carbon emissions reduction effect of shared e-bikes.

This is potentially because when the function of a place is monotonous, and transport service facilities density is low, people need to travel long distances to meet the needs of daily life, and a long e-bike sharing trip are more likely to replace a previous car trip. At the same time, many characteristics of places often come together. Specifically, attributes like relatively low land use density are always accompanied by low road density, undeveloped public transport systems, and low economic level. People living in these areas may not be rich enough to afford private cars. The emergence of shared e-bikes provides more low-carbon travel options for people in these areas, so e-bike sharing is more likely to replace high-carbon vehicles in those areas. When the function of land use is relatively mixed, facilities like workplaces, residences, shopping, eating and entertainment areas are located around the neighbourhood. Most trips that occur in these areas are relatively short because residents can meet most of their needs travelling only a short distance. Thus, people may choose cycling or walking to reach their destination instead of cars. Therefore, e-bike sharing trips in places with highly mixed land use replace fewer cars than in places with single land function. These findings could potentially help the decision making about where to launch and deploy e-bike sharing systems.

Table 4 Testing the correlation between features of the build environment and shared e-bikes' carbon emissions reduction: Regression results.

<i>Dependent variable: Carbon Emissions Reduction</i>			
Kunming	Kunming	Chengdu	Chengdu
OLS	SD	OLS	SD
(1)	(2)	(3)	(4)

***Independent Variables***

Land Use Diversity	-0.522*** (0.087)	-0.073 (0.101)	-0.477*** (0.051)	-0.060 (0.070)
Land Use Intensity	-0.104*** (0.038)	0.082* (0.049)	-0.105*** (0.036)	-0.003 (0.045)
Economic activity	-0.335*** (0.065)	-0.082 (0.182)	-0.224*** (0.026)	0.112 (0.113)
Public Transport	-0.107*** (0.027)	-0.039 (0.031)	-0.220*** (0.021)	-0.028 (0.029)
Road Density	-0.169*** (0.021)	-0.039 (0.026)	-0.049*** (0.013)	-0.001 (0.017)

***Control Variables***

E-bike Utilization Efficiency	1.925*** (0.403)	1.805*** (0.386)	1.093*** (0.155)	1.233*** (0.146)
Trip Duration	0.142*** (0.004)	0.133*** (0.004)	0.065*** (0.002)	0.059*** (0.002)
Population	-0.108*** (0.020)	-0.005 (0.024)	-0.033*** (0.010)	-0.017 (0.012)

***Lag Variables***

lag. Land Use Diversity		-0.605*** (0.147)		-0.331*** (0.088)
lag. Land Use Intensity		-0.199*** (0.065)		-0.099 (0.060)
lag. Economic activity		-0.083 (0.194)		-0.225* (0.116)
lag. Public Transport		-0.087* (0.045)		-0.186*** (0.037)
lag. Road Density		-0.147*** (0.036)		-0.032 (0.022)
lag. E-bike Utilization Efficiency		-1.770** (0.790)		-1.072*** (0.259)
lag. Duration		-0.010 (0.008)		0.0001 (0.004)
lag. Population		-0.106*** (0.032)		-0.002 (0.016)
Constant	3.339*** (0.493)	3.870*** (0.974)	3.909*** (0.184)	2.777*** (0.305)

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Observations	4,360	4,360	7,226	7,226
R2	0.256		0.171	

Log Likelihood		-6,155.734		-10,030.270
Akaike Inf. Crit.	12668.460	12,349.470	20968.460	20,098.550

Note: \*p<0.1, \*\*p<0.05, \*\*\*p<0.01

*Economic activity is night light index in log form; Public Transport is public transport stops density in log form; E-bike Utilization Efficiency is the turnover rate of shared e-bikes; Population is population density in log form.*

## 5.4 Sensitivity analysis

In the travel mode substitution model, the distance threshold between non-motorised travel and motorised travel may affect the carbon emission results so, in this section, we check the sensitivity of results to alternative distance threshold parameters ( $D_{t1}$ ) in the substitution model (Fig. 3). As mentioned in the results, travel distances from 1 km to 3 km are the primary competition interval of different travel modes. When the travel distance of an e-bike trip is less than 1 km, the probability of the trip replacing motorised vehicles is low; when the travel distance is greater than 3 km, the probability of the trip replacing non-motorised vehicles is pretty small. Therefore, we set two extreme scenarios by using the lowest and the highest values of the competition interval as the distance thresholds to generate the lower and upper limits for the carbon emissions reduction effect of shared e-bikes. The lower limit for the carbon emissions reduction effect is the extreme situation in which all trips with distances below 3 km replaced non-motorised travel modes, and the upper limit occurs when all trips with distances above 1 km replaced motorised travel modes. This paper then conducts regressions separately to check whether the variables are still significant and have the same negative correlations under extreme scenarios. It is found that the average carbon



emissions reduction per trip lies between 80g (lower limit) to 150g (upper limit). Additionally, even based on the upper limit of distance threshold (3 km) or the lower limit (1 km), the variables mentioned above are still significantly negatively correlated with the carbon emissions reduction effect (Table 5). The findings of the sensitivity analysis make the results of the paper more convincing.

Table 5 Testing the sensitivity of carbon emission results to alternative parameters.

	Dependent variable: <b>Carbon Emissions Reduction:</b>			
	D <sub>t1</sub> =1km		D <sub>t1</sub> =3km	
	Kunming	Chengdu	Kunming	Chengdu
	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
<b>Independent Variables</b>				
Land Use Diversity	-0.351*** (0.073)	-0.433*** (0.045)	-0.565*** (0.137)	-0.753*** (0.072)
Land Use Intensity	-0.125*** (0.032)	-0.074** (0.032)	-0.166*** (0.059)	-0.133*** (0.050)
Economic activity	-0.150*** (0.055)	-0.191*** (0.023)	-0.453*** (0.102)	-0.255*** (0.037)
Public Transport Stops	-0.089*** (0.022)	-0.196*** (0.019)	-0.191*** (0.041)	-0.330*** (0.031)
Road Density	-0.127*** (0.018)	-0.037*** (0.011)	-0.210*** (0.033)	-0.110*** (0.018)
<b>Control Variables</b>				
E-bike Utilization Efficiency	1.944*** (0.324)	1.141*** (0.134)	0.521 (0.614)	0.069 (0.219)
Trip Duration	0.102*** (0.003)	0.050*** (0.002)	0.170*** (0.006)	0.088*** (0.004)
Population	-0.105*** (0.016)	-0.035*** (0.009)	-0.137*** (0.030)	-0.068*** (0.014)
Constant	1.409*** (0.471)	3.491*** (0.224)	2.061** (0.885)	3.455*** (0.356)
Observations	4,360	7,226	4,360	7,226
R <sup>2</sup>	0.196	0.149	0.248	0.212

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*Note:*

\* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$

*Economic activity is night light index in log form; Public Transport is public transport stops density in log form; E-bike Utilization Efficiency is the turnover rate of shared e-bikes; Population is population density in log form.*

## **6. Conclusions and policy implications**

This is the first study, to the best of our knowledge, that analyses the potential carbon emissions reduction effect of shared e-bikes based on a large collection of shared e-bike trip data. In a sharing economy, e-bikes represent a new form of public transportation, and their potential for reducing emissions is worth exploring. In our study, we develop a travel mode substitution model to measure which mode is most likely to be substituted by shared e-bike trips, estimate the net carbon emissions change, and employ OLS and spatial lag models to explore how the environmental benefits of shared e-bikes can be boosted in which kinds of urban context. In terms of the proportion of replacement, shared e-bikes are more prone to reduce public transit and bike trips than car trips. However, the emissions reduction effect of shared e-bikes is stronger than the emissions increase effect resulting in a net reduction following the introduction of shared e-bikes.. On average, shared e-bikes result in a reduction in carbon emissions by 80–150 grams per trip. Assuming 0.18 million e-bike trips made in a city per day, this amounts to a reduction of carbon emissions by 14 tonnes–27 tonnes.

Regarding the spatial distribution of carbon emissions, although e-bike sharing reduces

carbon emissions overall, it still increases carbon emissions in some urban contexts, such as places with mixed and compact land use and easy accessibility. Therefore, when planning the spatial coverage of e-bike sharing schemes, areas characterised by, single land use, low density, low income and poorer public transit service should be prioritised for launching shared e-bike schemes. However, these areas are likely to be less profitable and less feasible if shared e-bike schemes are to be run in a for-profit manner.

Our results provide a reference for policy makers to promote the substitution of cars and inhibit the substitution of active travel by shared e-bikes. Nowadays, it is still controversial whether cities should allow the entry of shared e-bikes. Some big cities in China, like Beijing and Guangzhou, have forbidden the usage of shared e-bikes because of safety issues, while some cities like Kunming allow them. Chengdu forbids the usage of shared e-bikes in the urban centre, but permits them in the suburb. Places that will benefit from shared e-bikes could be identified from the perspective of reducing net carbon emissions. The corollary of this study for government and businesses for managing e-bike sharing schemes is that they need to be deployed in suitable locations with appropriate cycling infrastructure, especially in suburbs.

Although this study develops an innovative and quantitative calculation of the carbon emissions reduction effect of shared e-bikes based on big data analysis, there are some limitations. First, this study estimates the emissions change primarily based on the

shared e-bike trip dataset, and does not take into account the potential complementary effect on public transit and bikes, and the indirect substitution of cars by facilitating public transit in the last-mile connection, when calculating the net carbon emissions estimation. Secondly, the paper calculates the carbon emissions changes during the use of shared e-bikes, and does not consider the whole life-cycle carbon emissions of shared e-bikes, such as fleet manufacturing. Thirdly, shared e-bikes may be likely to save additional carbon emissions compared to a scenario where people would make these trips with private e-bikes. Fourthly, this paper has focused on the spatial heterogeneity of the carbon emissions of shared e-bikes, and did not analyse the changing characteristics of carbon emissions over time during a day. When the relevant data sources become available, such as the combination of survey data about the travel choice of citizens under different situations, a more accurate analysis will be carried out. Subsequent studies might explore the carbon emissions reduction effect of shared e-bikes in more depth, to further unravel the impact of shared e-bikes on carbon emissions. These discussions may make the findings more comprehensive and give more precise policy and business implications.

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