Transportation Research Part D 85 (2020) 102412

Contents lists available at ScienceDirect

Transportation Research Part D

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

Electric bicycle mode substitution for driving, public transit, conventional cycling, and walking

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ARTICLE INFO

Keywords:
Electric bicycle
E-bike
Mode substitution
Mode shift
Sustainable transportation

ABSTRACT

The key to understanding the impacts of electric bicycles (e-bikes) on congestion, the environment, and public health is to what extent they displace travel by other (particularly motorized) modes of transportation. This study investigates the mode substitution effects of e-bikes, based on a *meta*-analysis of 38 observations of mode substitution patterns reported in 24 published studies from around the world. Median mode substitution reported in the literature is highest for public transit (33%), followed by conventional bicycle (27%), automobile (24%), and walking (10%), but varies widely with interquartile ranges of 31% for auto and 44% for public transit. Weighted mixed logit model results indicate a trade-off in substitution of motorized modes, with significantly greater displacement of public transit in China and greater displacement of auto travel elsewhere (Europe, North America, and Australia). Newer studies report greater displacement of driving and walking and less displacement of conventional bicycle trips, which indicates a positive trend. Results also suggest that e-bike adoption may be part of a transition away from conventional bicycle use, while displacing auto and transit travel after adoption. Further studies are needed in the context of evolving forms of micromobility, particularly outside of northern Europe and China.

1. Introduction

Electric bicycles, commonly known as “e-bikes”, have recently been the subject of increased interest from transportation engineers and urban planners around the globe. This paper addresses the key determinant of the environmental impacts of e-bikes: mode substitution. We use *meta*-analysis to synthesize the findings of e-bike studies from around the world and examine the expected displacement of travel by other modes – in particular driving and transit, which determine the potential for avoided emissions from e-bike adoption.

E-bikes have been a popular mode of transportation in Asia since the 2000 s, and are gaining popularity in North America and Europe in recent years (An et al., 2013; Dekker, 2013; Fishman and Cherry, 2016). E-bikes offer space-efficiency, flexibility, and environmental benefits similar to conventional bicycles, yet require much less effort by the rider to operate. They are more expensive than conventional bicycles, but typically less expensive to acquire and maintain than an automobile. As such, e-bikes have the potential to encourage more people to cycle for work and recreation, leading to reductions of congestion and traffic-related emissions and possibly increases in physical activity and health (Bourne et al., 2018; Fishman and Cherry, 2016; Fyhri and Fearnley, 2015; Kroesen, 2017).

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https://doi.org/10.1016/j.trd.2020.102412

Available online 08 June 2020
1361-9209/

E-bikes are commonly defined as bicycles with electric pedal-assistance. Restrictions on weight, power, and speed of e-bikes vary by jurisdiction, typically 250 to 500 W maximum motor power and 25 to 40 km/hr maximum speed with assistance. Power-assisted two-wheelers that do not have operable pedals, often called scooters, are generally viewed as a separate vehicle type and regulated differently in many jurisdictions (Aono and Bigazzi, 2019; Cairns et al., 2017; Fishman and Cherry, 2016; MacArthur and Kobel, 2014). Reported usage of e-bikes varies considerably by location. Travelers in Asia, particularly China, were among the earliest adopters of e-bikes, and are still the largest e-bike market in the world, while European and North American countries have seen substantial growth in e-bike sales over the past decade (Fishman and Cherry, 2016; Weinert et al., 2007a).

A key factor for the potential impacts of e-bikes on congestion, the environment, and public health is to what extent they displace travel by other (particularly motorized) modes of transportation (Bourne et al., 2018; Sundfør and Fyhri, 2017; Weiss et al., 2015). This topic has been investigated in dozens of studies over the past two decades, and the results tend to be highly localized (Fishman and Cherry, 2016; Kroesen, 2017). We still lack a systematic understanding of the factors influencing e-bike mode substitution patterns. To address that issue, this study investigates the mode substitution effects of e-bikes in displacing travel by automobile, public transit, conventional bicycle, and walking. A *meta*-analysis of published studies of mode substitution by e-bike users is undertaken to understand travel displacement in a range of settings.

2. Method

2.1. Literature search

WorldCat and Google Scholar databases were searched in January 2020 using the keywords “e-bike”, “electric bike”, and “electric bicycle”. Search results were reviewed, and additional sources identified from the reference lists of those sources. Government and university reports were included, in addition to peer-reviewed journal articles. To be included in the *meta*-analysis, the studies had to explicitly report quantitative empirical data on mode shift, substitution, or replacement from e-bike use. They also had to report data in formats that could be transformed into proportions of e-bike use displacing travel by each substitute mode: either numbers or proportions of e-bike trips, travel distance, or travelers. Calculating mode shift from mode shares required reporting of mode shares for both e-bike and a substitute mode before and after e-bike adoption. Alternative data and reporting formats that led to study exclusion were general indications of mode use frequency (“daily”, “rarely”, etc.), mode preferences (e.g., likelihood of cycling as Likert scores), and statistical relationships or models without explicit substitution data, such as in (Haustein and Møller, 2016; Kroesen, 2017; Moser et al., 2018; Plazier et al., 2017; Popovich et al., 2014). In order to mitigate some of the effects of response bias, a second inclusion criterion was that the studies had to measure mode substitution from actual e-bike use. Determination of the substitute modes could be based on hypothetical questions, but the e-bike use could not be hypothetical.

Ultimately, out of dozens of published articles and reports that investigate or discuss travel behaviour with e-bike use, 24 publications present empirical data on e-bike mode substitution: 13 from northern Europe (Astegiano et al., 2015; Dekker, 2013; Hendriksen et al., 2008; Hiselius and Svensson, 2017; Jones et al., 2016; Kamper et al., 2016; Lee et al., 2015; Sun et al., 2020; Van Cauwenberg et al., 2019) – including 4 non-English-language European reports presented in Cairns et al. (2017) from Kairos, Mobiel 21, Sustrans, and VCD; 8 from China (An et al., 2013; Cherry and Cervero, 2007; Cherry et al., 2016; Lin et al., 2018, 2017; Montgomery, 2010; Weinert et al., 2007b; Xu et al., 2014); 2 from North America (Langford et al., 2013; MacArthur et al., 2018); and 1 from Australia (Johnson and Rose, 2015).

2.2. Measurements of mode substitution

Table 1 summarizes the mode substitution measurement approaches of included studies (those for which full English language texts were available). The most common methods of recruiting e-bike riders were interception during travel and public promotion or advertisement of the study. Some studies also recruited directly from e-bike shops, e-bike customer registries, or e-bikeshare system users. One study avoided recruitment by doing secondary data analysis on an existing national household travel survey panel that included questions about e-bike ownership. The intercept survey methods generally achieved higher sample sizes than other recruitment methods.

The questions used to elicit mode substitution information are described in Table 1; note that most surveys were not administered in English and so very few studies report verbatim question wording. The mode substitution questions generally fall into two categories: reported travel mode prior to e-bike adoption (“previous mode”) and hypothetical travel mode choice if e-bikes were to be unavailable (“alternative mode”). Alternative mode questions referred both to future trips and past trips after e-bike adoption. The one study using existing travel survey data assessed previous travel mode by comparing travel mode shares in the years immediately before and after acquiring an e-bike.

Depending on the survey design, mode substitution was either assessed for specific e-bike trips (typical for intercept surveys and studies using travel diaries), or for e-bike trips in general. Participants describing substitution for general e-bike trips were sometimes allowed to select multiple substitute modes (referred to as non-exclusive in Table 1); other study designs required a single substitute mode to be identified. Not all studies included the same alternative modes, but four (auto driver or passenger, bus or rail public transit, conventional cycling, and walking) appear in most studies, and are modeled in this analysis. Few studies distinguish auto driver from auto passenger, or different types of public transit, so they are also combined in this analysis. Some studies also report mode substitution for taxi and other modes (usually moped, motorcycle, or simply “other”), as well as new or induced travel (trips that would not be/have been made without an e-bike).

Table 1
Measurement methods of e-bike mode substitution reported in the literature.

Study	Location	Data year	Number of participants	Recruitment	Mode substitution question[1]	Substituted e-bike activity	Data reporting
(An et al., 2013)	Shanghai, China	2011	470	Intercept survey	Travel mode for this trip before acquiring an e-bike, and future travel mode if e-bikes were forbidden/banned	Intercepted trip	Proportion of participants reporting each alternative mode
(Astegiano et al., 2015)	Ghent, Belgium	2014	100	Unspecified (not intercept)	Back-up travel mode participants would use for e-bike trips, if e-bikes were not available	Each trip in a 1–2 week travel diary	Proportion of trips (across all participants) by each alternative mode
(Cherry et al., 2016)	Kunming, China	2006, 2008, 2010, & 2012	303–801 (varying by year)	Intercept survey	Travel mode for the same trip before owning an e-bike, and travel mode that would be taken now in the absence of an e-bike	Intercepted trip	Proportion of participants reporting each alternative mode
(Dekker, 2013)	Amsterdam, Netherlands	2012	22	Recruited from e-bike shops	Participants purchased an e-bike to replace travel by what mode(s)	General trips	Proportion of participants reporting each alternative mode, and proportion of total e-bike travel distance (across all participants) by each alternative mode
(Hiselius and Svensson, 2017)	Sweden	2011	321	Recruited from customer register of an e-bike retailer	Main travel mode replaced by e-bike usage	General trips (for five trip purposes)	Proportion of participants reporting each alternative mode
(Johnson and Rose, 2015)	Australia	2012	69	Public promotion/ advertisement (age ≥ 65)	Travel mode(s) that would be used if an e-bike were not available (non-exclusive)	General trips (for four trip purposes)	Proportion of participants reporting each alternative mode
(Jones et al., 2016)	Netherlands and UK	2013	22	Public promotion/ advertisement	Main travel mode for e-bike trips, before e-bike purchase	General trips	Proportion of participants reporting each alternative mode
(Kamper et al., 2016)	Germany	2014	382	Unspecified (not intercept)	Travel mode participants would have used for each trip before purchasing an e-bike	Each trip in a 4 week travel log (GPS)	Proportion of trips and e-bike distance (across all participants) by each alternative mode
(Langford et al., 2013)	Knoxville, USA	2012	22	Recruited from e-bikeshare system users	What would have been the alternative travel mode for each trip	Each trip taken using the e-bikeshare system	Proportion of trips (across all participants) by each alternative mode
(Lee et al., 2015)	Netherlands	2012	217	Public promotion/ advertisement	Travel mode that would be used if an e-bike were not available	Each trip in a travel diary (unspecified duration)	Proportion of trips (across all participants) by each alternative mode
(Lin et al., 2018, 2017)	Nanjing, China	2014	403	Intercept survey	Travel mode(s) previously used prior to e-bike acquisition, and alternative travel mode(s) in the future if e-bikes were unavailable (non-exclusive)	General trips	Proportion of participants reporting each alternative mode
(MacArthur et al., 2018)	USA and Canada	2017	1796	Public promotion/ advertisement	Travel mode that would have been used if an e-bike were not used	Each of 3 most recent trips	Proportion of trips (across all participants) by each alternative mode
(Montgomery, 2010)	Jinan, China	2008	1171	Intercept survey	Previously used travel mode before acquiring an e-bike, and substitute travel mode that would be used if not e-bike	General trips	Proportion of participants reporting each alternative mode
(Sun et al., 2020)	Netherlands	2015	107	Existing national panel dataset	None (reported travel behaviour before and after e-bike purchase)	Each trip in a 3-day travel diary in two successive years	Average mode share (by distance) across participants before and after acquiring an e-bike
(Van Cauwenberg et al., 2019)	Flanders, Belgium	2016	357	Public promotion/ advertisement	E-bike trips were previously made by which travel mode(s) (non-exclusive)	General trips	Proportion of participants reporting each alternative mode
(Weinert et al., 2007b)	Shijiazhuang, China	2006	460	Intercept survey	Travel mode if e-bike were no longer an option	Intercepted trip	Proportion of participants reporting each alternative mode

(*continued on next page*)

Table 1 (*continued*)

Study	Location	Data year	Number of participants	Recruitment	Mode substitution question[1]	Substituted e-bike activity	Data reporting
(Xu et al., 2014)	Xi'an, China	2012	576	Intercept survey	Previous travel mode and future mode if shifting away from e-bike	Unclear	Proportion of participants reporting each alternative mode

[1] as described in paper/report, not exact question wording.

Data reporting in these studies takes two common forms. When the survey elicits substitute modes for a single trip per participant, the results are reported as the proportion of participants substituting each mode (which is equivalent to the proportion of trips). When the survey elicits substitute modes for multiple trips per participant, the results are reported as the proportion of trips substituting each mode (across all participants). Two studies also reported the proportion of total e-bike travel distance (across all participants) substituting each mode. Finally, the study using existing travel survey data reported average mode share (by distance) across participants before and after acquiring an e-bike.

The results data reported in the literature were processed to allow comparison across studies and *meta*-regression. The mode substitution measure is intended to represent the aggregate share of e-bike use displacing each of the other modes. Note that this measure is not necessarily the same as the amount of displaced travel by the substituted modes because destinations, distances, and vehicle occupancy can also change with mode substitution.

With consideration of the available data, no distinction is made in the analysis between reported measures of the proportions of trips and the proportions of participants. These measures are equivalent in the studies that assess a single trip per participant. For studies assessing general e-bike travel, this simplification neglects differences in the frequency of e-bike trips among participants, which could affect the results if the frequency is systematically related to the substitute modes.

Another simplification is made to include non-exclusive response surveys, in which participants could indicate multiple modes substituted by e-bike travel in general. These (three) studies report the proportions of participants substituting each mode, which sum to more than 1 because there were multiple positive responses per participant. The reported data are rebalanced as the number of positive responses for each mode out of the total number of positive responses (so that they sum to 1 across modes) – i.e., $\frac{p_i}{\sum_i p_i}$ where p_i is the proportion of participants reporting substitution of mode i. This adjustment neglects differences in the frequency of e-bike trips and the number of substitute modes per participant (the effects of which would offset each other if they are positively correlated). Finally, for the study reporting only mode shares before and after e-bike adoption, the proportion of e-bike travel substituting for each mode is taken as the respective reductions in mode share as a proportion of the e-bike mode share after adoption.

2.3. Meta-regression

Meta-regression is the technique of using regression models to analyze variation in the size of an effect of interest based on data from the literature. By combining results from multiple publications, *meta*-regression can provide information about a true effect size and also identify study-invariants that influence outcomes (Borenstein et al., 2011; Stanley and Doucouliagos, 2012). In this study, mode substitution for e-bike travel is investigated using mixed logit models with the dependent variable of the reported proportion of e-bike use in each study displacing travel by each substitute mode (as four separate models for substitution of auto, public transit, conventional bicycle, and walking).

Weights are applied in *meta*-regression to reflect the quality and reliability of data from each study, often represented as the inverse of the reported variance. Most publications in this study do not report variance in mode substitution, and so sample sizes are used as weights instead. This approach assumes larger samples are more reliable, a common alternative approach (Agresti, 2003). Random effects by study are included to address unexplained heterogeneity due to omitted variables and correlation among observations reported in the same publication (Borenstein et al., 2011; Stanley and Doucouliagos, 2012).

Model fitting is carried out using the “glmer” function in the “lme4” package in R (Bates et al., 2015). Model specification excludes explanatory variables above a significance threshold of $p = 0.05$. In addition to the mode substitution data (dependent variable) described in the previous section, the following information was extracted from each study for potential explanatory variables: publication details (year, venue), study location, survey methods, sample size and characteristics, and e-bike ownership status (owned, rented, or loaned). Through preliminary data analysis, several potential explanatory variables were excluded because of inconsistent reporting across studies, multicolinearity, or lack of variability among studies (particularly related to study design and location). Ultimately, four variables were retained for regression modelling: year of data collection (as an integer from the earliest year, 2006), mode substitution data type (as a binary variable for previous versus alternative mode, as described above), e-bike ownership (as a binary variable for privately owned versus rented or loaned), and study region. Due to the rarity of studies outside of China and Europe, and the similarity of transport systems in Europe, North America, and Australia, study region in the analysis is defined by a binary variable for China versus elsewhere.

“Previous mode” and “alternative mode” were measured in 16 and 15 studies, respectively; the seven studies reporting both types of data are included twice in the analysis as separate observations (with a dummy variable for data type and random effects by study). One study (Cherry, Yang, Jones, & He, 2016) reports data from surveys in four different years (without participant retention); those data are treated as four separate observations. Another study (Johnson and Rose, 2015) only reports separate result for commute and local trips; those data are also treated as separate observations.

3. Results

The regression dataset includes 38 observations from the 24 studies (with multiple observations where multiple surveys or data types are reported in the same study – see above). The full data set is provided in the Supplemental Material. The variables used in regression modelling are summarized in Table 2 and described above. The mode substitution data come from an 11-year period (2006 to 2017), with a mean lag between data collection and publication of 3.0 years (median of 2.0).

Almost all data collection took place in urban settings, in cities of varying size. The data collected in China come from six different

Table 2
Explanatory variables used in *meta*-regression.

Variable	Values
Year of data collection (from 2006)	0 to 11,median of 6
Study location in China (vs. Europe, North America, or Australia)	50% TRUE
Alternative mode (vs. previous mode) substitution data type	50% TRUE
Study sample used privately owned e-bikes (vs. rented or loaned)	95% TRUE

large cities, with Kunming and Shanghai the most frequently studied. In Europe, reported data come from the Netherlands, Belgium, Germany, the UK, Sweden, and Austria (in decreasing frequency). Most (68%) of the observations are reported in peer-reviewed journal articles. The sample sizes range from 22 to 1796, with a median of 393. Two thirds of the studies report sample gender statistics, which range from 22% to 67% female (median of 48%).

Fig. 1 summarizes the distributions of mode substitution reported across studies. The circles in the figure represent statistical outliers more than $1.5 \times IQR$ beyond the interquartile range (IQR). Results vary widely, with IQR of 31% for auto and 44% for public transit. Median mode substitution is highest for public transit (33%), followed by conventional bicycle (27%), auto (24%), walking (10%), and new or induced trips (1%). All the distributions have positive skew. Not shown in Fig. 1, there were 23 reports of taxi mode substitution (0–12%, median of 4%) and 29 reports of other mode substitution (0–17%, median of 3%).

Fig. 2 gives the correlation matrix among mode substitution proportions reported across studies. Auto mode substitution has a strong negative correlation with public transit substitution, indicating that studies reporting higher substitution of one tend to report lower substitution of the other. Hence, there is a trade-off in motorized mode displacement, where studies tend to report higher proportions of one or the other, but not both. Transit substitution is moderately negatively correlated with walk and conventional bicycle substitution, indicating weaker trade-offs in substitution of those modes. Auto substitution has little (linear) relationship with substitution of the active modes. Similarly, substitution of walking and conventional bicycle are only slightly negatively correlated.

Meta-regression results are summarized in Table 3, which gives the estimated mixed logit model coefficients for each of the four modal models. Pseudo-R^2 values (based on null model log likelihood) vary widely across modes, from 0.06 for walking to 0.62 for conventional bicycle. Results indicate a substantial difference in motorized mode substitution in China versus elsewhere, with odds ratios of 0.25 for auto substitution and 6.82 for transit substitution in China versus elsewhere. These differences are likely due to greater overall auto mode share in the European, North American, and Australian study cities and greater transit mode share in the Chinese study cities, which in turn corresponds to higher-density study locations in China. Study region was not significant for the substitution rates of the active modes, although the estimated signs suggest less substitution in China.

The year variable was significant in three of the models, indicating greater auto and walking substitution in newer studies (odds ratios of 1.11 and 1.08 per year, respectively) and less conventional bicycle substitution (odds ratio of 0.89 per year). This result may indicate an early adopter effect, with earlier studies capturing initial adoption by existing cyclists, and later studies capturing later (but still early) adopters from other modes (Wolf and Seebauer, 2014). If this indicates a broader trend, it would mean increasing marginal benefits of further e-bike adoption.

Due to the earlier time scale of e-bike adoption in China, an interaction effect between region and year was tested for all four models. The interaction effect was significant at $p < 0.05$ for auto (positive effect, with odds ratio of 1.22) and at $p < 0.10$ for conventional bicycle (negative effect, with odds ratio of 0.84). Thus, there is some evidence that the trend toward auto substitution is stronger in China (possibly related to China's recent increase in auto ownership), and the trend away from conventional bicycle substitution is stronger elsewhere (possibly associated with a higher proportion of e-bike use by early adopters outside of China).

"Alternative mode" data type is a significant variable for three of the models in Table 2, indicating that mode shift for hypothetical travel if e-bikes were unavailable is higher for motorized modes and lower for conventional bicycles than mode shift from previous

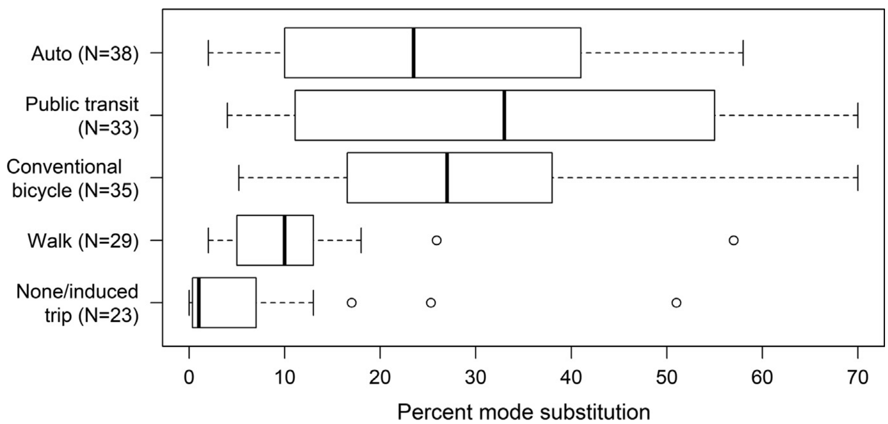

Fig. 1. Boxplots of mode substitution reported across studies (circles indicate statistical outliers).

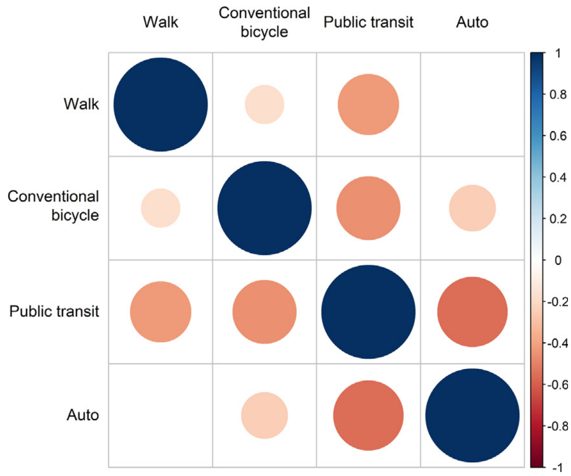

Fig. 2. Correlation matrix of mode substitution reported across studies (color intensity and size of circles are proportional to correlation coefficients).

Table 3
Regression models of proportion of e-bike mode substitution

Variable	Proportion of e-bike use displacing: Auto	Public transit	Conventional bicycle	Walking
Intercept	−3.22	−1.93	−0.74	−1.25
Year of data collection (from 2006)	0.10	NS⁻	−0.12	0.08
Study location in China	−1.37	1.92	NS⁻	NS⁻
Alternative mode (vs. previous mode)	0.85	0.32	−1.08	NS⁺
E-bikes privately owned (vs. rented/loaned)	2.49	NS⁺	NS⁺	−1.47
Sample size:observations (unique studies)	38 (24)	33 (20)	35 (22)	29 (16)
Psuedo-R^2	0.40	0.23	0.62	0.06

Notes: all parameters other than intercepts significant at $p < 0.05$; $NS^{+/-}$ indicates variables excluded because not significant at $p < 0.05$ (and with positive/negative coefficients when included); Psuedo-R^2 based on log likelihood of null model.

travel before e-bike adoption. In other words, studies report more mode shift from conventional bicycles at initial e-bike adoption than if e-bikes were to become unavailable, and vice-versa for auto and public transit. This result could be due to travelers replacing a conventional bicycle with an electric bicycle (so that conventional bicycle was no longer available after adoption), or an artifact of the wording of survey questions on mode substitution. If the former, then it indicates that e-bike adoption has a larger effect on conventional bicycle ownership than auto ownership, as reported in the Netherlands (Kroesen, 2017). The result could also indicate self-selection, where e-bike adopters are looking to shift away from conventional bicycles to an (at least partially) motorized mode, and e-bikes serve that purpose. In other words, e-bike travel may replace trips that were *previously made* by conventional bicycle but then *would have been made* by auto or transit (Ling et al., 2015).

Finally, e-bikes that are privately owned are reported to have a negative impact on walking substitution (odds ratio of 0.23) and positive impact on auto substitution (odds ratio of 12.11) versus e-bikes that are rented or loaned. A privately owned e-bike indicates a substantial financial investment by the traveler, whereas a rented or loaned e-bike does not. This result could reflect the wealth of the sample, something that was not included explicitly in the analysis. It could also reflect trip purpose differences, with more walkable local and recreational trips made on rented or loaned e-bikes, and more long commute and utilitarian trips made on privately-owned e-bikes.

4. Discussion

The *meta*-regression analysis presented above indicates that for e-bike travel:

- There is a trade-off in substitution of motorized modes, with much greater displacement of transit travel in China and of auto travel in Europe, North America, and Australia,
- Newer studies report greater displacement of driving and walking and less displacement of conventional bicycle trips, which could be a positive trend for e-bike benefits, and
- E-bike adoption may be part of a transition away from conventional bicycle use, but still displacing auto and transit travel.

These findings provide insights about the collective information reported in 24 studies of e-bike usage around the world, but the results and the models themselves should be applied and interpreted with caution. The models are explanatory, not predictive, and cannot reliably predict mode shift in any one city. In particular, the "year of survey" variable is unreliable to predict trends outside of the study years in the dataset.

The models were estimated with relatively few observations due to the limited number of studies reporting usable substitution data. The sample size limited the number of explanatory variables that could be included in the models. Other factors related to the study design (e.g., recruitment method and sample characteristics) and the study location (e.g., regional mode shares, bicycle infrastructure, and transit service level) are likely important for substitution patterns as well. Substitution patterns in Europe, North America, and Australia are likely different, but insufficient data were available to separate those regions. Even within Europe, studies were concentrated in northern Europe. No data were available from South America or Africa. The disproportionate representation of the Global North could be partly due to lack of access to non-English-language studies, but the larger effect is probably the preponderance of research emerging from those countries, as well as greater interest in and use of e-bikes. Further research on e-bike use is needed to improve our understanding of impacts in locations outside of northern Europe and China.

Many other individual-level factors influence mode substitution, including age, income, gender, education, vehicle/bicycle ownership, and quality of the transit services available for a given trip (Cherry et al., 2016; Lin et al., 2018). Systematic differences in these factors among study populations would aggregate up to some of the differences among studies reported here. The lack of consistent reporting on study sample attributes prevented inclusion of most of those factors in this analysis. For example, female proportion of the study sample was only reported in 2/3rd of the studies, and so not included in the regression. Adding that variable to the analysis (and thus removing 1/3rd of the observations) yields a significant coefficient only for auto substitution (negative, with odds ratio of 0.05 and $p = 0.009$). The estimated effects for substitution of the other modes are positive for transit and negative for conventional bicycle and walking, though not significant at $p < 0.05$. Alternative models were also estimated excluding non-peer-reviewed studies from the dataset, but it did not substantially change the results.

In addition to a limited amount of study data, the results reported here are vulnerable to internal validity issues in the extracted study data, such as the validity of self-reported mode substitution questions, as described in Kroesen (2017). The "previous" mode data could be influenced by faulty recall or social desirability bias; the "alternative" mode data could be similarly affected by social desirability or strategic bias, among others. More reliable data for causal inference could be obtained from longitudinal travel studies, but the literature is dominated by cross-sectional studies.

Another weakness of the existing studies threatening internal and external validity is sample recruitment; few studies have undertaken robust random sampling, and most rely on convenience samples with some amount of participant self-selection. Thus, even if the studies weight for sample socio-demographics, there are still potential representation issues for causal inference and generalization to broader impacts. E-bike users more willing or eager to participate in a survey may be disproportionately shifting from certain other modes – for example, those making choices seen as more socially desirable by shifting from driving versus shifting from conventional bicycles. A further issue for generalizing to the broader population is that the studies used in the analysis, and the vast majority of the literature, draw data from samples of early adopters. It is likely that early adopters have different mode substitution patterns from later adopters (as suggested above by the survey year variable in the regression).

Several studies have collected longitudinal data on e-bike interventions, including a randomized trial, e.g. (Fyhri et al., 2017; Fyhri and Fearnley, 2015; MacArthur et al., 2017; Moser et al., 2018). However, they do not specifically report mode substitution or mode share data and so could not be included in this analysis. Fyhri and Fearnley (2015) report cycling mode share before and after an e-bike intervention, but do not differentiate e-bike from conventional bicycle use, and do not report shares of other modes. Sun et al. (2020), which was included in the analysis, report observed mode shares before and after e-bike adoption, but not based on an intervention. Hence, the data from that study are less vulnerable to response biases (enhancing internal validity), but still vulnerable to early adopter self-selection (limiting external validity).

Regarding the findings, the results describe the proportion of e-bike travel substituting for each alternative mode, but not necessarily the amount of displaced travel by those modes. If multiplied by the number of e-bike trips, the results indicate the displaced number of trips by substituted modes. However, mode substitution may also involve changes in trip destinations and distances, and so the same substitution proportions may not apply for travel distances. The connection is further complicated by possible changes in vehicle occupancy, since auto mode includes both drivers and passengers. Hence, if 24% of e-bike travel is displacing travel by auto, 100 km of e-bike travel may not be displacing 24 km of vehicle travel. The reduction in vehicle-kilometers traveled could be higher if further destinations would have been chosen for the auto trip, or lower if some of the displaced auto travel would have been in multi-occupant vehicles.

As more research on e-bike adoption emerges, *meta*-analyses such as this will be important to generalize findings and identify patterns. Another factor to consider in future research is the types of e-bikes and other forms of micromobility available in each study. Research on e-bikes may be limited, but research on electric push scooters and other new forms of mobility are almost non-existent, and we are years away from being able to examine interactions among these modes in a broad *meta*-analysis such as this. Meanwhile, we know that e-bikes have a role in reducing motorized travel, despite substantial substitution of walking and conventional bicycle trips.

CRediT authorship contribution statement

Alexander Bigazzi: Conceptualization, Methodology, Investigation, Data curation. **Kevin Wong:** Investigation.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trd.2020.102412.

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