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Electrifying Choices: How Electric Bicycles Impact on Mode Choice and CO_2 Emissions

By Thomas Hagedorn*
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This paper analyzes (i) the influence of electric bicycle ("e-bike") ownership on transport mode choice and (ii) how a change in e-bike ownership affects carbon dioxide (CO_2) emissions in Germany. Using longitudinal data from household surveys from 2016 to 2022, we first conduct a trip-level analysis with a mixed multinomial logit model (MMNL model) to estimate mode choice probabilities. The results show that the change in e-bike ownership significantly affects travel behavior, by increasing the likelihood of choosing an e-bike as means of transportation by 14.6 percentage points (p.p.), while correspondingly decreasing the likelihood of choosing other modes, especially conventional bicycles by 5.6 p.p., as well as car and public transportation by about 4 p.p. each. Second, by using observed changes in individual distances traveled and transport-mode-specific emissions values, we calculate net emissions savings per person after acquiring an e-bike. These savings amount to 526.9 kg CO_2 per person and year.

Keywords: E-Bikes, transport mode choice, CO_2 emissions, longitudinal data, mixed multinominal logit model.
JEL: R40, C33, Q59.

I. Introduction

The promotion of active mobility is important in order to improve the efficiency of the transportation system, reduce emissions and thus contribute to a more sustainable transportation system (Buehler et al., 2019; European Commission, 2024; Fyhri and Fearnley, 2015; Pucher and Buehler, 2008; Wessel, 2023). In this context, electric bicycles ("e-bikes") are a promising way to increase the modal share of cycling, as they enhance the comfort of cycling through an integrated battery that amplifies the cyclist's pedaling power and thus enables cycling longer distances with less physical effort and time. In the context of our study, we define e-bikes as pedelecs (pedal electric cycle) with a maximum speed of 25 km/h (Fishman and Cherry, 2016; Philips et al., 2022). In Germany, conventional bicycles and e-bikes have become an important means of transportation for daily mobility and leisure activities. In 2023, 1.85 million conventional bicycles and 2.1 million e-bikes were sold in Germany (ZIV, 2023), making it the first year in which more e-bikes were sold than conventional bicycles. This trend indicates a growing preference for e-bikes among consumers, so that it is important to study whether increasing sales would also translate into increasing usage of e-bikes.

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In recent years, the rising popularity of e-bikes has generated a wave of research on how e-bikes are changing travel behavior (see for example Bigazzi and Wong (2020), Cherry and Cervero (2007), Cherry et al. (2016), Fishman and Cherry (2016), Fyhri and Fearnley (2015), John et al. (2018), Jones et al. (2016), Kroesen (2017), Lee et al. (2015), Ling et al. (2017), Sun et al. (2020), Winslott Hiselius and Svensson (2017), Wolf and Seebauer (2014), and Zhou et al. (2023)). A short coming of most of these studies is that they use self-recruitment methods, like web-based surveys or experiments in which e-bikes are provided temporarily to participants. These approaches are susceptible to self-selection bias, as the participants in these studies are often those who already have a strong affinity with cycling and thus might not reflect the broader population. To overcome these methodological limitations, cross-sectional data from national household travel surveys provide a detailed, and in many cases, representative overview of mobility habits at a given point in time (e.g. Arning and Kaths, 2024; Kohlrautz and Kuhnimhof, 2024; Kroesen, 2017). However, cross-sectional data have the limitation of only allowing for comparisons between individuals. They do not allow for an evaluation of changes in individual mode choice behavior over time, and thus it can be difficult to infer causality. This lack of longitudinal perspective limits the understanding of long-term impacts and trends in transportation behavior (de Haas et al., 2023; Sun et al., 2020; Zhou et al., 2023), so that "[...] future research should strengthen longitudinal data research to acquire a more profound comprehension of the commonalities and differences in transportation mode selection"(Zhou et al., 2023, p. 103891).

To contribute to the literature, we analyze the influence of e-bike ownership on transport mode choice over time, and how a change in the likelihood of choosing an e-bike could affect CO_2 emissions. To the best of our knowledge, there is currently no research that specifically analyzes the effects of e-bike ownership on transport-mode choice in Germany using longitudinal data. Closing this research gap is particularly relevant, as it could provide important insights into the changing mobility behavior in the context of increasing popularity of e-bikes in Germany. In particular, motorized private transport is by far the dominant mode of transport in Germany with a modal split of 73.6 % in 2019 and is responsible for the majority of transport-related CO_2 emissions (Allekotte et al., 2020; Federal Ministry for Digital and Transport, 2023). Shifting individuals from carbon-intensive to low-carbon modes of transport (e.g. cycling or walking) therefore has potential to reduce CO_2 emissions (Brand et al., 2021; Creutzig et al., 2018).

In our empirical analysis, we use longitudinal data from household surveys in Germany from 2016 to 2022. In the first part of our analysis, we identify the impact of e-bikes on transport mode choice by exploiting variation in e-bike ownership, and controlling for other factors such as sociodemographic and trip-specific variables. We estimate mode choice behavior using an MMNL model. The main regression analysis shows that variation in e-bike ownership over time significantly changes travel behavior by encouraging the use of e-bikes and reducing the use of car, conventional bicycle, Bus, Tram and Metro (BTM) and walking as the main mode of transport. This applies especially to short and medium distances. The robustness check confirms that individuals tend to substitute conventional bicycle trips and car trips after acquiring an e-bike.

In the second part of our analysis, we calculate the net CO_2 emissions savings per person after acquiring an e-bike, which suggests that e-bike ownership contributes to a reduction in CO_2 emissions through a shift to less carbon-intensive modes of transport. Our results provide important insights on individual mode-choice behavior and can thus be helpful for transport planners and policy makers in promoting e-bikes and thereby more environmentally friendly transport behavior.

The following article is structured as follows. Section II provides an overview of the background literature. Section III outlines our data and methodology. The results of the regression analyses and the subsequent robustness checks are presented in Section IV. Section V analyzes the environmental impact of a change in e-bike ownership, and Section VI discusses the results and concludes.

II. Background Literature

The substitution behavior of e-bike users and the factors influencing it have been widely discussed in the literature in recent years.[1] According to Yin et al. (2024), e-bike ownership can reduce car use by up to 19 % in households that own both an e-bike and a car, compared to households that only own a car. In bicycle-oriented cultures, e-bikes often complement car ownership and are seen as a substitute for bicycle ownership (de Haas et al., 2022; Plazier et al., 2023). In terms of substitution behavior, the mode of transport that is substituted by e-bikes varies by country, depending on local transport options. E-bikes tend to replace short car trips in car-dominant regions (e.g. Bigazzi and Wong, 2020; Fyhri and Fearnley, 2015; John et al., 2018; Jones et al., 2016; Winslott Hiselius and Svensson, 2017; Wolf and Seebauer, 2014; Yin et al., 2024), as well as conventional bicycles and car trips in a bicycle-oriented culture (e.g. Netherland) (see for example Haustein and Møller, 2016; Kroesen, 2017; Lee et al., 2015), and public transport in regions with a comprehensive public transport system (e.g. Cherry and Cervero, 2007; Cherry et al., 2016; Fishman and Cherry, 2016). However, many of these studies rely mainly on self-selection methods or cross-sectional data, which limits their ability to make within-individual comparisons over time, such as changes in transport-mode choice. A longitudinal perspective enables a more profound comprehension of the commonalities and differences in transport-mode selection.

To the best of our knowledge, only two studies use longitudinal data, and both use data from the Netherlands Mobility Panel. Sun et al. (2020) investigated the impact of purchasing an e-bike on travel behavior based on four years of panel data. The results indicate that the year after purchasing an e-bike, the use of the conventional bicycle decreased significantly. Car use, walking and the use of public transport appear to decline to a lesser extent. One limitation of the study is the lack of a comparison group for e-bike users. The comparison group is only included with the general population at the beginning of the study, but not after purchase. Without an ongoing comparison group, it is difficult to isolate the effect of e-bike ownership from other variables that might influence travel behavior (e.g. seasonal variations or social trends). Using a cross-lagged random intercept panel model with 5 waves of the national panel dataset, de Haas et al. (2022) suggest that at a general level (including all trip purposes), the substitution effect of e-

[1] See for example An et al. (2013), Arning and Kaths (2024), Arning et al. (2023), Bigazzi and Wong (2020), Cherry and Cervero (2007), Cherry et al. (2016), de Haas et al. (2022), Fyhri and Fearnley (2015), Fyhri and Sundfør (2020), Haustein and Møller (2016), Hiselius and Svenssona (2014), Huang et al. (2024), Kämper et al. (2016), Kohlrautz and Kuhnimhof (2024), Kroesen (2017), Lee et al. (2015), Ling et al. (2017), McQueen et al. (2020), Plazier et al. (2023), Reck et al. (2022), Schneider (2023), Sun et al. (2020), Weinert et al. (2007), and Yin et al. (2024).

bikes on car and public transport trips is not significant and that e-bikes only significantly reduce the use of conventional bicycles. If only commuter trips are considered, the results indicate that e-bikes also substitute for cars in addition to conventional bicycles. A limitation of the study by de Haas et al. (2022) is that only aggregated indicators such as the number of trips by a certain transport mode were used, which does not allow for an investigation of mode substitution at the trip level.

Furthermore, mode substitution is closely related to the environmental impact of e-bike use. E-bikes have the potential to significantly reduce CO_2 emissions by promoting sustainable travel behavior (Berjisian and Bigazzi, 2019; Haustein and Møller, 2016; Hiselius and Svenssona, 2014; Kämper et al., 2016; Li et al., 2023; McQueen et al., 2020; Moser et al., 2018; Philips et al., 2022; Winslott Hiselius and Svensson, 2017). Although e-bikes produce more CO_2 than conventional bicycles, due to higher emissions from the manufacturing process (e.g. battery) and charging the battery, their emissions are lower than those of public transport, and significantly lower than those of cars (McQueen et al., 2020). If cycling replaces the car, this contributes significantly to achieving national and international climate goals. Philips et al. (2022) estimated an average annual reduction in CO_2 emissions of 580 kg per person from using an e-bike instead of a car. Kämper et al. (2016) quantitatively analyze the potential modal shift effect and climate impact of e-bike usage through a field test in Germany. Accordingly, switching from car to e-bike could save 150 g of greenhouse gas per passenger kilometer.

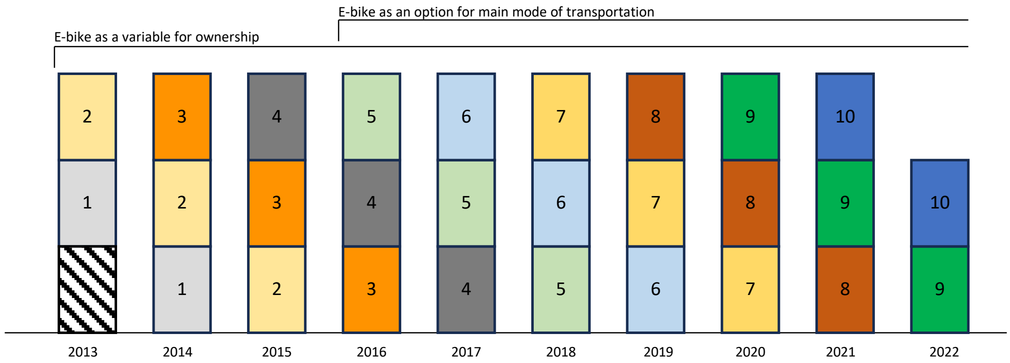
To summarize, because of the limited literature on the substitution effects of variations in e-bike ownership, there are two major research gaps. First, there is currently no study that specifically analyzes the effects of e-bike ownership on mode choice in Germany, and second, on how a change in e-bike ownership contributes to a reduction in CO_2 emissions in Germany. Given the identified research gaps, this present study contributes to the literature in the following ways. First, we analyze how a change in e-bike ownership affects the choice of main mode of transport, by conducting a trip-level analysis using an MMNL model with longitudinal household survey data from 2016 to 2022. Second, we specifically calculate the observed net CO_2 emissions savings per person after acquiring an e-bike, so as to analyze how a change in e-bike ownership contributes to a reduction in CO_2 emissions.

III. Data and Methodology

A. Data

In this paper we use data from the German Mobility Panel (MOP). The MOP is a longitudinal study on the travel behavior of the German population and has been conducted every year since 1994. The MOP is designed as a rotating household-based sample over a period of three years as depicted in Figure 1. Households participate for three consecutive years, after which they drop out, and are replaced by new households. The data includes socioeconomic and demographic characteristics of individuals and households, as well as vehicle ownership and weather. Each year, the household members are asked to report their travel information in detail (i.e. distance traveled, transport modes, trip purpose, start and end times) in a travel diary for seven consecutive days, excluding school and bank holidays. Since 2013, e-bike ownership has been included as an individual-specific variable in the MOP ("Who owns an e-bike?"). From 2016 onwards,

Figure 1. : Schematic Overview of Annual Survey Waves and Cohorts (2013 to 2022)

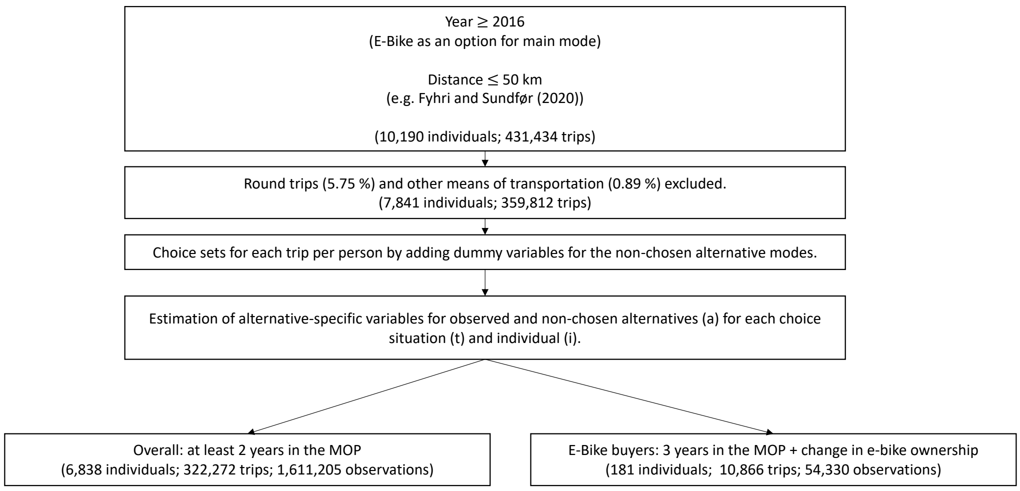


Cohorts are defined as groups of people (households) who were surveyed in the same wave. The dataset for one year consists of three different cohorts. We only consider households that are included in the dataset for at least two years.

e-bikes are considered as a potential main mode of transport, which corresponds to the mode used for the longest part of the trip.[2]

To prepare the MOP data for our analysis, we thus filtered the data to include only years after 2016, when e-bikes became a viable option for the main mode of transport (see Figure 2). Following the literature (Fyhri and Sundfør, 2020;

Figure 2. : Data Preparation



Sun et al., 2020), we restrict the trips to those less than 50 kilometers. Within this distance range, all considered modes (car, conventional bicycle, e-bike, BTM, walking) are realistically usable, hence enabling a meaningful comparison of the different modes. It should be noted that in the MOP, a trip is defined as any movement from the current location to a specific destination. Continuing a trip or returning to the departure location is considered as a separate trip. Each new

[2] The term "main mode of transport" is defined in such a way that each trip is represented by only one main mode, based on the definition from the German Institute for Economic Research (Kloas and Kuhfeld, 2009).

trip must begin where the previous one ended. We only focus on car, conventional bicycle, BTM, and walking, so we exclude modes of transport that are labeled as "others" (0.89 %), such as electric scooters, and we exclude round trips (5.75 %).

Our mode choice model is based on discrete choice theory. Accordingly, we need to generate choice sets that describe individual choices among the five alternatives (car, conventional bicycle, e-bike, BTM, walking). To do this, we create a binary variable *choice*, which takes on the value 1 for the chosen alternative and 0 for the non-chosen alternatives. Then, for each choice situation, we need to compute the trip-specific *cost* and *duration* variables for the non-chosen alternatives. The detailed computation is outlined in Appendix A.A1. We also include the Oxford Covid Stringency Index OxCGRT to control for the effects of the Covid-19 pandemic and the subsequent government intervention on mobility (Mathieu et al., 2020).

Table 1 summarizes all the variables used to estimate the model. In order to investigate possible mode shifts after buying an e-bike, we prepare two datasets. The dataset "Overall" encompasses all individuals who have been in the dataset for at least two years, including e-bike owners (i.e. those who purchased or owned an e-bike during the period in the MOP sample) and those who have never owned an e-bike. The dataset "E-Bike buyers" only includes those individuals who have been in the dataset for three years and purchased an e-bike in the second year, or in the third year before the data collection.

Table 1—: Variables Used for Model Estimation

Variable	Unit	Min	1st Qu.	Mean	3rd Qu.	Max
Trip-specific						
distance	km	0.05	1.50	7.39	9.70	50.00
duration	min	3.58	7.45	16.57	21.33	210.02
cost	€	0.00	0.16	2.02	2.40	15.88
Weather						
rain	binary			0.46		
temperature over 10 degrees	binary			0.58		
Socio-demographic						
senior	binary			0.26		
commuter	binary			0.25		
high economic status	binary			0.64		
area type city	binary			0.68		
e-bike ownership	binary			0.12		
car availability regular	binary			0.68		
bicycle ownership	binary			0.75		
Others						
Covid Stringency Index	index	0.00	0.00	15.84	35.29	83.33

B. Methodology

Discrete choice techniques are often used in the analysis of problems related to transportation (Bolduc et al., 2010; Liao et al., 2024; McFadden and Train, 2000; Reck et al., 2022; Small and Verhoef, 2007; Train, 2003). To identify the impact of e-bike ownership on mode choice, we exploit the variation in e-bike ownership and control for other factors, such as socio-demographic and trip-specific variables. Similar to Liao et al. (2024), McFadden and Train (2000), Reck et al. (2022), and Train (2003), we use the mixed multinominal logit model (MMNL model) to account for the panel structure of our data. For a more detailed description of the mathematical formulations, we therefore refer to these papers.

The MMNL model helps us to overcome three limitations of the multinomial logit model (MNL model). First, the model allows for random variation in taste, i.e. it can account for individual differences in preferences that are not explained by the factors that can be controlled for. Second, it allows for correlation of unobserved factors over time by the same individual. This means that it can capture persistent characteristics, such as a person's general preference for certain modes of transport. Third, the model can deal with unrestricted substitution patterns, e.g. it can handle complex substitution behavior between different transport modes (Train, 2003). Thus, the model can take into account the heterogeneity of tastes in mode choice across individuals.

The utility U that individual i receives from alternative a in choice situation t is divided into two parts: a deterministic part V and a random part ϵ, whereby the deterministic part V can be further expressed as

$$U_{iat} = V_{iat} + \epsilon_{iat} = x_{iat} \cdot \beta_i + \gamma_a \cdot \text{ebike\_ownership}_{it} + \tilde{z}_{it} \cdot \delta_a + \epsilon_{iat}. \tag{1}$$

x_{iat} is a vector of alternative-specific variables (e.g. cost and duration) that vary by individual, alternative, and choice situation, with the corresponding random coefficients β_i that vary over individuals with density $f(\beta)$, accounting for the person's taste (see, e.g., Liao et al., 2024; Train, 2003). $\gamma_a \cdot \text{ebike\_ownership}_{it}$ represents the case-specific variable e-bike ownership, with its fixed alternative-specific coefficients that vary across individuals and choice situations, indicating how e-bike ownership influences the likelihood of choosing each mode. The remaining case-specific variables are $\tilde{z}_{it} \cdot \delta_a$, where $\tilde{z}_{it}$ is a vector and δ_a are their fixed alternative-specific coefficients. In our case, $\tilde{z}_{it}$ includes socio-demographic information (e.g. trip purpose, person-specific information, vehicle ownership), trip-specific attributes such as distance, weather and the Covid Stringency Index. ϵ_{iat} is a random term that follows a type I extreme value distribution. For a complete overview of all explanatory variables used to estimate the regression model, we are refering to Table 1.

According to Reck et al. (2022) and Train (2003), the probability of individual i choosing alternative a in choice situation t, conditional on the random parameter β_i, can be expressed as

$$P_{iat}(\beta) = \frac{exp(x_{iat} \cdot \beta_i + \gamma_a \cdot \text{ebike\_ownership}_{it} + \tilde{z}_{it} \cdot \delta_a)}{\sum_{a=1}^{A} exp(x_{iat} \cdot \beta_i + \gamma_a \cdot \text{ebike\_ownership}_{it} + \tilde{z}_{it} \cdot \delta_a)}.$$

After integrating P_{iat} over the mixing distribution $f(\beta)$, we obtain the unconditional choice probability, where d equals the number of random parameters:

$$P_{iat} = \int P_{iat}(\beta) f(\beta) d\beta. \tag{2}$$

The probabilities are approximated by simulation, so that the simulated likelihood for the i_{th} case is

$$L_i = \prod_{t=1}^{T} \sum_{a=1}^{A} d_{iat} \hat{P}_{iat},$$

where d_{iat} is equal to 1 for the chosen alternative at choice situation t and 0 otherwise. The following computation $\hat{P}_{iat}$ is used to approximate the probabilities in Equation 2, where β^m are the random parameters drawn from density $f(\beta)$ and M is the number of random draws:

$$\hat{P}_{iat} = \frac{1}{M} \sum_{m=1}^{M} P_{iat}(\beta^m). \tag{3}$$

As this process is repeated for up to $M = 1000$ draws, the predicted mode-choice probabilities represent the average probability of choosing a specific main mode of transport.

IV. Analysis of Mode Choice Behavior

A. *Descriptive Analysis*

We begin our analysis with some descriptives of the MOP dataset. Figure 3 indicates that the overall increasing trend in e-bike sales in Germany is also present in the MOP dataset. In 2022, more than 21 % of the overall sample population owned an e-bike, compared to roughly 6 % in 2016. Correspondingly, ownership of conventional bicycles decreased over time from 71.2 % to 61.7 %.

Figure 3. : Conventional Bicycle and E-Bike Ownership by Year

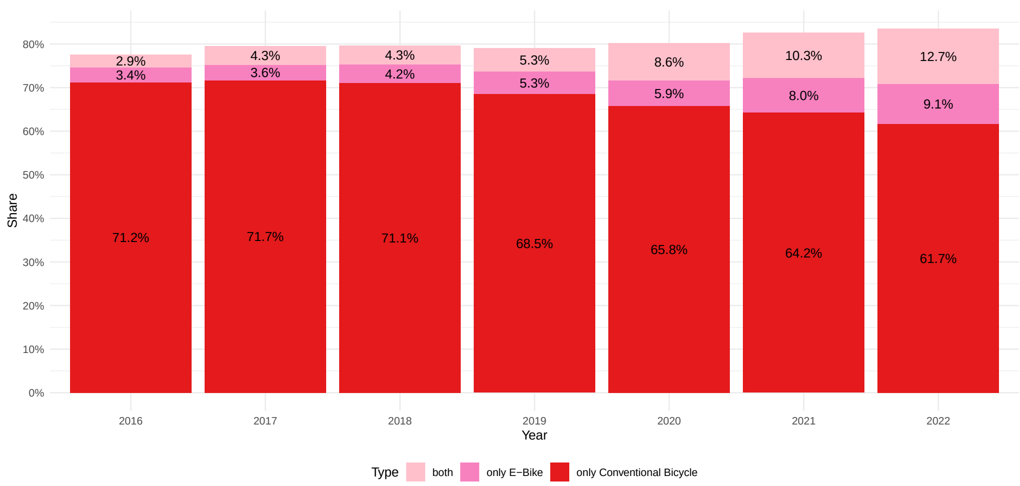
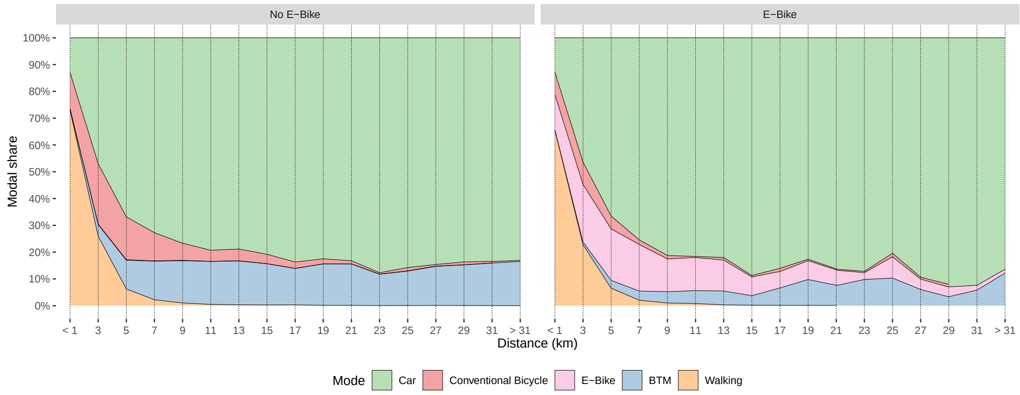


Figure 4 illustrates the impact of e-bike ownership on the frequency of use of main transportation modes within different distances for the overall dataset. On the left we see the group of individuals who do not own an e-bike, while on the right we see the group of individuals who do. Not surprisingly, e-bike owners use it quite frequently, especially for short and medium distances up to 20 km. The corresponding use of cars, conventional bicycles and BTM is lower, indicating

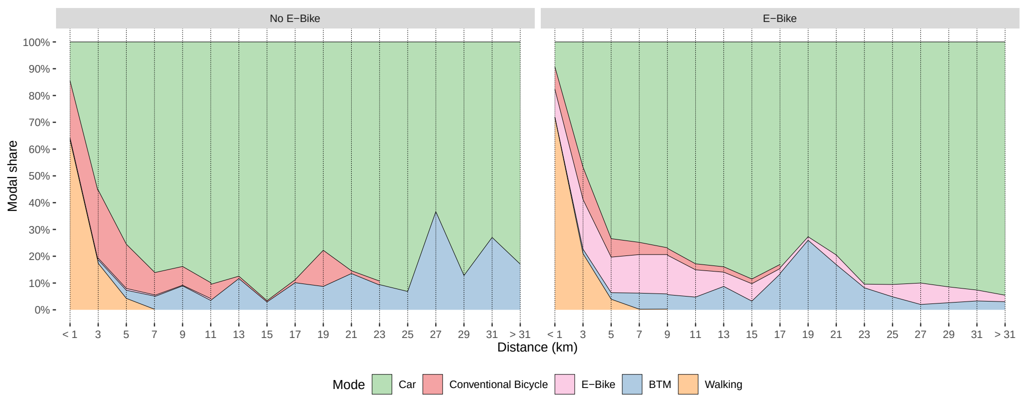
Figure 4. : Mode Share by Distance of "Overall" Dataset



that e-bikes might have a positive impact on the environment through mode shifts. In contrast, the mode share for walking is similar between both groups. For longer distances (20–50 km), e-bike ownership seems to have less influence on mode choice, but we still observe that e-bikes are chosen for longer distances compared to conventional bicycles.

Next, we look at how the use of each mode changes when e-bike ownership changes, i.e. we only consider individuals who switch from not owning an e-bike to owning one within the observation period. Therefore, we use the "E-Bike buyer" dataset. This allows us to compare travel patterns before and after acquiring an e-bike (Sun et al., 2020). In Figure 5, it seems that after acquiring an e-bike,

Figure 5. : Mode Share by Distance of "E-Bike buyer" Dataset



it can replace other modes of transportation, especially for short and medium distances. This pattern is consistent with and confirms the results observed in Figure 4.

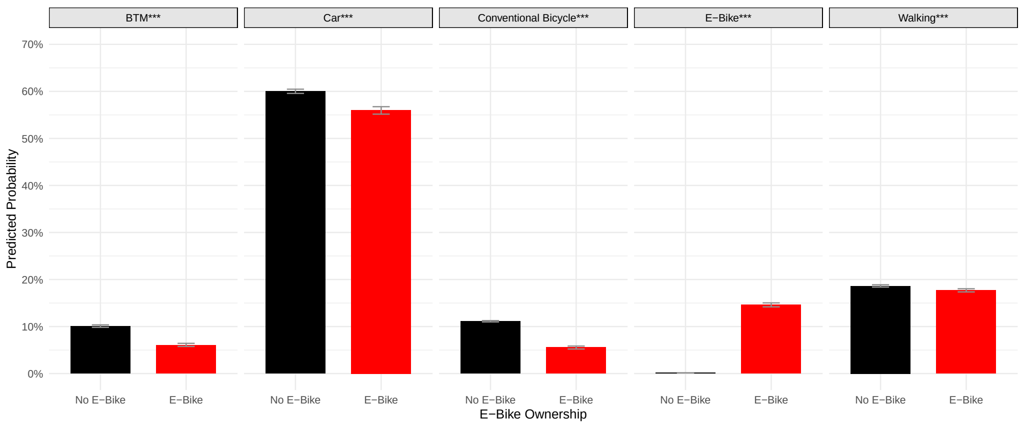
In conclusion, the above results indicate that e-bike ownership seems to affect the mode choice for e-bikes, car, BTM and conventional bicycle. Next, we want to verify these results with our regression model.

B. *Regression Model*

Results

To verify our results from the descriptive analysis, we use the MMNL model outlined above to determine the impact of e-bike ownership on mode choice. Since the choice probabilities are a nonlinear function of the estimated parameters, we estimate the effect of the variable *ebike_ownership* on the outcome of the MMNL model to obtain average predicted probabilities for each status of e-bike ownership, holding the other variables constant (Williams, 2012). Figure 6 illustrates the average predicted mode choice probabilities for variation in e-bike ownership, based on the MMNL model. We begin by using the "Overall" dataset to increase validity and generalizability, and to provide a comprehensive comparison. We then use the "E-Bike buyer" dataset as part of our robustness check. The results show that owning an e-bike increases the likelihood of choosing an e-bike as the main mode of transportation by 14.56 p.p.. On the other hand, e-bike ownership reduces the average choice probability of a conventional bicycle by 5.6 p.p., of a car or BTM by 4 p.p., and walking by 0.9 p.p.. The differences in predicted mode

Figure 6. : Average Predicted Probabilities and 95 % Confidence Intervals of Mode Choice



Significant difference between "No E-bike" and "E-Bike" based on Chi-Square Tests. $^{*}p < 0.05,^{**}p < 0.01,^{***}p < 0.001$

choice probabilities between e-bike owners and non e-bike owners are statistically significant according to chi-squared tests and the delta method (see Appendix A.A2). Hence, the regression analysis confirms and validates the findings of the descriptive analysis, i.e. that e-bike ownership affects mode choice for cars, BTM and conventional bicycles.

Since transport-mode choice depends on distance (see Section IV.A), we estimate average probabilities of e-bike ownership status at different distances and find that the impact of e-bike ownership on mode choice differs greatly, depending on distance. For this reason, Figure 7 provides point estimates of choosing a specific main mode of transportation at given distances, differentiated between e-bike ownership and no e-bike ownership. Figure 7A shows that the likelihood of choosing the e-bike as the main mode of transport increases with distance when owning an e-bike (red line), until around 5 km (predicted choice probability of

20.89 %) and then begins to decrease steadily with distance until 25 km, where the predicted choice probability is around 0.04 %. This confirms the results of the descriptive analysis that e-bike ownership increases e-bike use especially for short and medium distances. For non e-bike owners (black line), the predicted probability of choosing the e-bike as the main mode of transport is almost constant, but negligible[3]. Owning an e-bike reduces the likelihood of choosing a conventional bicycle (Figure 7B), car (Figure 7C) or BTM (Figure 7D) as the main mode of transportation, with different magnitudes depending on distance. The largest decrease in the likelihood of choosing a conventional bicycle as the main mode of transport occurs at a distance of 3 km, where the average predicted likelihood drops by almost 10 p.p. when owning an e-bike. In addition, the largest reduction in the average predicted likelihood of choosing a car is observed at a distance of 5 km, with a difference of almost 7 p.p.. The most significant reduction in the likelihood of choosing (BTM) is found at 7 km, with a reduction of 6 p.p. when owning an e-bike. Finally, the predicted probability of choosing walking (Figure 7E) as the main mode of transportation remains relatively stable and does not differ significantly between e-bike and non e-bike owners.

In summary, e-bike ownership has a significant impact on transport-mode choice. For short and medium distances, e-bike owners tend to substitute conventional bicycle trips, car trips and also BTM trips with the e-bike. For longer distances, the influence of e-bike ownership decreases, indicating that e-bikes are mainly used for shorter and medium distances. This shift could have important environmental implications, as it indicates a shift towards more sustainable modes of transport for shorter and medium distances only.

Robustness Check

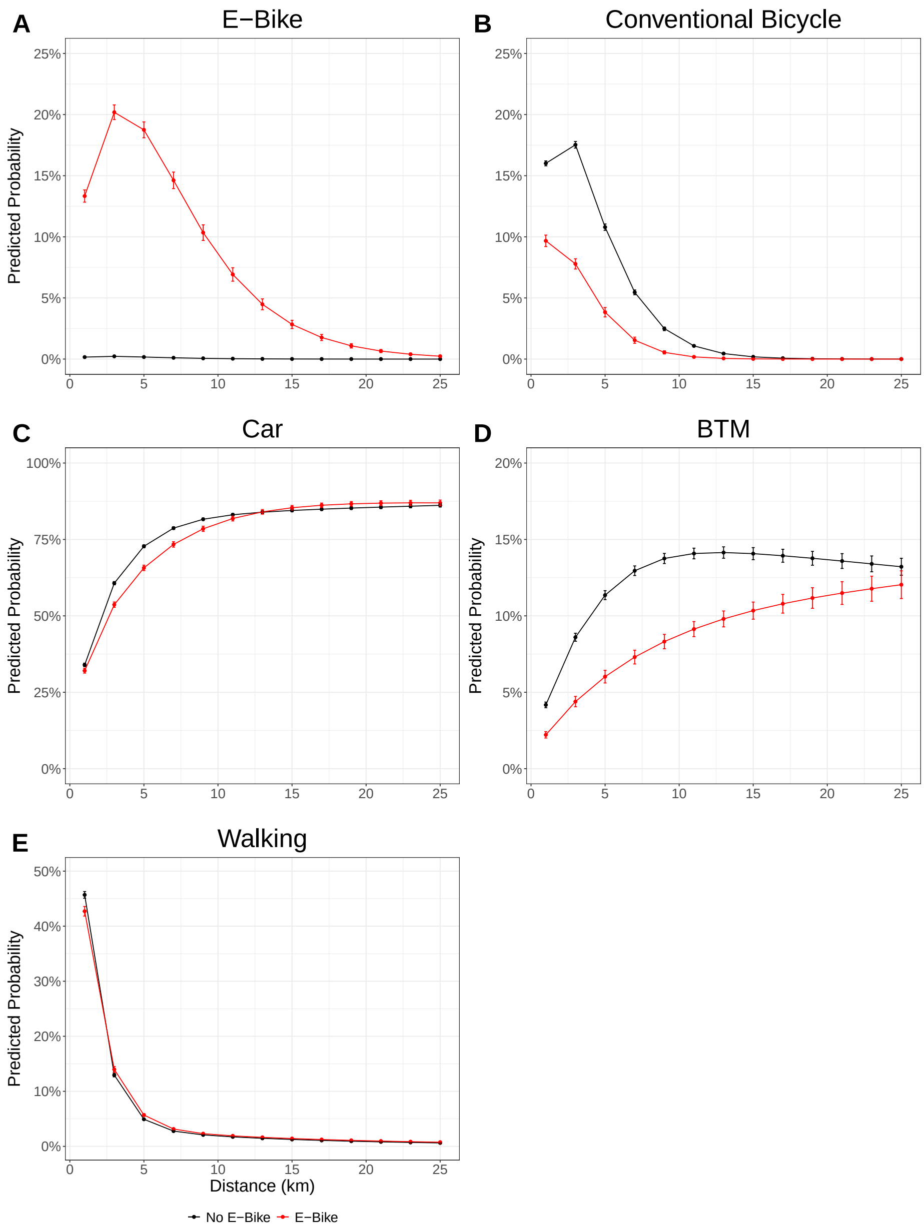
Estimating a regression model across subsamples is a traditional approach to analyzing robustness in empirical work (Catherine et al., 2023). For example, theory may predict that the baseline effect estimate should be larger (or smaller) for groups with certain characteristics. Estimating a regression separately for different groups is then a simple way to assess the validity of interpretation of the results. One limitation from the study of Sun et al. (2020) is the lack of a consistent comparison group to isolate the effect of e-bike ownership. To overcome this limitation in our study, we assess the robustness of the main analysis (Chapter IV.B) by re-estimating the impact of e-bike ownership on transport mode choice using the "E-Bike buyers" dataset. We can thereby check whether the estimates remain similar in the restricted sample. This approach ensures the reliability and consistency of the results by considering only individuals who purchased an e-bike during the study period. In summary, most of our results are confirmed (see Appendix A.A3 and A.A4), indicating that e-bike ownership indeed exerts a significant impact on mode-choice behavior. Individuals tend to substitute conventional bicycle trips and car trips after acquiring an e-bike.

V. Analysis of Environmental Impact

The impact of the variation in e-bike ownership on the sustainability of the transportation system depends not only on the modes they replace, but also on

[3] Since the variable *ebike_ownership* is limited to personal ownership, the slight increase could be derived from shared use or the borrowing of e-bikes.

Figure 7. : Predicted Probabilities and 95 % Confidence Intervals of Mode Choice by Distance



the emissions associated with those modes. There are a few studies on the environmental impact of e-bikes (Bucher et al., 2019; Cherry et al., 2009; McQueen et al., 2020; Philips et al., 2022; Reck et al., 2022; Winslott Hiselius and Svensson, 2017). The results of these studies show that the use and purchase of e-bikes has a positive impact on the environment and the potential to reduce CO_2 emissions in the transportation sector. To contribute to this strand of the literature, we use data from the "E-Bike buyers" dataset to calculate the observed total CO_2 emission savings per person before and after acquiring an e-bike.

Since our regression model calculates the predicted mode-choice probability, depending on e-bike ownership, but not the change in distances traveled per main mode, we follow Winslott Hiselius and Svensson (2017) and calculate the observed change in distances traveled by each individual, independent of the results from the regression model. To do so, we calculate the average annual distance traveled $\overline{d}_{a,k}$ for each mode of transport a, with and without e-bike ownership $k \in \{0, 1\}$. Then, based on the mode-specific emission value θ_a, we calculate the total emissions per individual E_k:

$$E_k = \sum_a \overline{d}_{a,k} \cdot \theta_a = \sum_a (52 \cdot \frac{1}{N} \sum_{i=1}^{N_{a,k}} d_{i,a,k}) \cdot \theta_a \tag{4}$$

where $d_{i,a,k}$ is the total weekly distance traveled by each individual i and N is the total number of individuals in the dataset. For the mode-specific emission value θ_a, we build on previous work by the International Transport Forum (ITF, 2020), which recently conducted a comprehensive analysis, measuring the environmental impacts of new and established transport modes. The study provides emission values for life-cycle performance based on the technical characteristics, operation and maintenance of the modes, as well as vehicle manufacturing. These values allow for a more precise differentiation of mode characteristics and thus the determination of weighted mode-specific emission values (ITF, 2020). The mode-specific emission value θ_{BTM} equals 72 g CO_2/pkm, representing the average emissions from bus, tram and metro. θ_{Car} equals 208 g CO_2/pkm and is a weighted mode-specific emission value that takes into account the proportion of different engine types and car sizes in the sample. The mode-specific emission values for the other modes are: θ_{Bicycle} equals 17 g CO_2/pkm, $\theta_{\text{E-Bike}}$ equals 34 g CO_2/pkm, and θ_{Walking} equals 0. Table 3 shows the average annual emissions for individuals, and the net change in emissions resulting from the variation in e-bike ownership by mode.

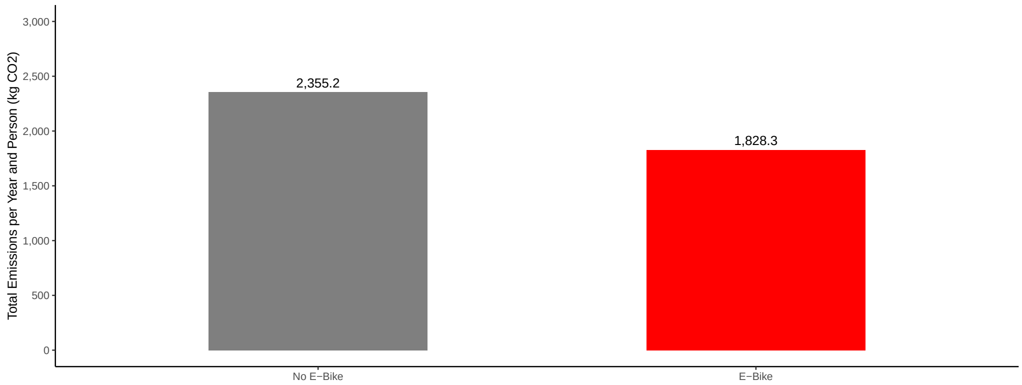
Table 3—: Annual Emissions for E-Bike Ownership Variation per Mode

	BTM	Bicycle	Car	E-Bike	Walking	Total
Emission "No E-Bike"	109.1	11.1	2,234.4	0.6[1]	0.0	2,355.2
Emission "E-Bike"	46.2	3.4	1,753.6	25.2	0.0	1,828.3
△ kg CO_2 per person	-62.9	-7.7	-480.8	24.6	0.0	-526.9

[1] Since "No e-bike" is limited to personal ownership of e-bikes, the value could be derived from shared use e-bikes.

We find that owning an e-bike contributes to a more sustainable transportation system, mainly because more emission-intensive modes such as car and BTM are used less. As shown in Figure 8, the average annual emissions saved by each person after purchasing an e-bike is 526.9 kg CO_2 per year, demonstrating the positive environmental impact of e-bike ownership. These results could also indicate that e-bike ownership indeed leads to a substitution of car and BTM trips, rather than merely inducing new e-bike trips.

Figure 8. : Annual Change in CO_2 Emissions After the Purchase of an E-Bike



VI. Discussion and Conclusion

In summary, we run a MMNL model and find that e-bike ownership significantly impacts transportation mode-choice in Germany. Owning an e-bike significantly reduces the likelihood of choosing BTM, conventional bicycles, cars, or walking, but increases the likelihood of choosing the e-bike as the main mode of transportation, especially for short distances up to 15 km. The robustness check confirms a substitution effect for conventional bicycles and cars. For longer distances, the influence of e-bikes as the main mode of transportation decreases. This shift also has important environmental implications, especially for those individuals who purchase an e-bike within the survey period. The calculation of net emissions savings per person after acquiring an e-bike suggests that owning an e-bike contributes to a reduction in emissions of up to 526.9 kg CO_2 per year.

When interpreting these results, one should carefully take into account the local context, i.e. whether e-bikes are more likely to partly replace the dominant modes of transportation in a given mobility system. Therefore, we relate our results to those from countries with similar mode shares and data availability. To this end, we focus on two studies from the Netherlands that use longitudinal data to examine the substitution of e-bikes for other modes of transport, where cars and conventional bicycles also have the two largest shares in the modal split. In the Netherlands, about 69 % of passenger-kilometers are by car and 8 % by bicycle (KiM, 2020). In Germany, about 80 % of passenger-kilometers are by car and about 5 % by bicycle (Allekotte et al., 2020). Sun et al. (2020) find that after purchasing an e-bike, conventional bicycle and car use decline significantly, while walking and public transport are affected to a lesser extent one year after the purchase of an e-bike. de Haas et al. (2022) find that e-bike trips primarily reduce conventional bicycle trips, which is seen as an unwanted effect from a policy point of view. However, a limitation of their study is that only aggregated indicators such as the number of trips by a certain transport mode were used, which does not allow for an investigation of mode substitution at the trip level. Our MMNL model also indicates that the variation in e-bike ownership over time significantly changes travel behavior by increasing the use of e-bikes and reducing the use of other modes, especially conventional bicycles (5.6 p.p.) and cars (around 4 p.p.) and thus is in line with the literature. Moreover, we find that for short and medium distances up to 15 km, owning an e-bike decreases the predicted probability of choosing a car or a conventional bicycle as the main mode of transportation, while increasing the probability of choosing an e-bike. E-bike ownership has less impact on the main mode-choice probability for longer distances. Our results are consistent with the literature, as most trips fall within the range of up to 15 km, making the e-bike a relevant travel option (Plazier et al., 2023; Sun et al., 2020).

As our study also investigates the environmental impact of e-bike ownership, it is important to note that the net carbon impact of increased e-bike use depends, among other things, on the mode of transportation which is replaced. Winslott Hiselius and Svensson (2017) give an indication of the magnitude of energy efficiency potential of e-bike use by reducing car mileage in Sweden. Based on the assumption of 48 travel weeks per year, the CO_2 emissions that can be reduced are 349 kg CO_2 per person per year. Pierce et al. (2013) investigate, for the National Health Service in the UK, how the purchase of an e-bike to replace a car for both commuting and home visits affects CO_2 emissions. They found an average reduction of 748 kg CO_2 per year from switching to the e-bike. McQueen et al. (2020) estimate the regional impact of e-bikes on greenhouse gas emissions. If an individual in Portland (USA) replaced 15 % of their person miles traveled with an e-bike, and total person miles and trips remained constant, a single e-bike could save an average of 225 kg CO_2 per year. Philips et al. (2022) estimates the maximum reduction of CO_2 by substituting private car trips with e-bikes. The average saving is 0.58 tons of CO_2 per year for each person who uses an e-bike to replace car km to their maximum capability. In our study, we calculate the observed net CO_2 emissions savings from switching to an e-bike per person per year at about 526.9 kg, which is roughly 6.6 % of the average annual total CO_2 emissions per capita in Germany (Ritchie et al., 2022). This value is within the range indicated in previous studies, thus validating our findings and demonstrating the substantial potential for CO_2 emissions reduction.

As we focus only on the variation in e-bike ownership, future research could expand our approach and extend the study to consider how cars and e-bikes complement each other in dual-mode ownership (Yin et al., 2024). Although dual-mode ownership is not the focus of our research, it would be interesting for future studies to explore possible effects in a car-oriented culture such as Germany.

In our study, we provide important information on individual mode choice in relation to e-bike ownership. This information can help transportation planners and policy makers to promote e-bikes in order to achieve the goals of the National Cycling Plan 3.0. This plan aims to double the number of kilometers cycled in Germany by 2030 compared to 2017, thus supporting the key objectives of the Pan-European Cycling Master Plan.

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Appendix

A1. Estimation of the Variables Duration and Cost

For each choice situation, we need to compute the trip-specific variable *duration* for the non-chosen alternatives. To do this, we build subsets for each transport mode and estimate travel times for each non-chosen alternative mode, using a linear regression model based on the recorded distance of actual observed trips and controlling for various factors:

$$\begin{aligned} duration_{it} = &\beta_0 + \beta_1 \cdot \text{distance}_{it} + \beta_2 \cdot \text{distance}_{it}^2 + \beta_3 \cdot \text{age}_{it} + \\ &\beta_4 \cdot \text{daytime}_{it} + \beta_5 \cdot \text{area\_type}_{it} + \epsilon_{it} \end{aligned}$$

where ϵ represents the error term. For each alternative, the difference in travel time between the chosen alternative and the predicted travel time from the linear model was calculated to check for potentially erroneous information provided by survey participants or data-entry errors in the dataset. Similar to Ennen and Heikler (2020), if the difference is outside the defined threshold (i.e. the estimated travel time is twice as long or half of the average observed travel time), those trips are no longer considered (10.25 %).

The variable *cost* for the chosen and non-chosen modes is based on the distance traveled and the specific cost per kilometer ξ_a for each mode. We assume that the distance traveled within the choice situation remains constant regardless of the mode (Croissant, 2020):

$$cost_{iat} = distance_{it} \cdot \xi_a,$$

with ξ_{car} : 0.31 €/km[4], $\xi_{\text{E-Bike}}$: 0.12 €/km[5], ξ_{Bicycle} : 0.06 €/km[6], ξ_{Walking} : 0 €/km. The variable $cost_{BTM,it}$ is calculated from the individual network tariffs of the transport association v. For simplicity, we use the average price of the transport association's fare levels. We also distinguish between no season ticket and season ticket:

1. No season ticket:

$$cost_{BTM,vit} = \begin{cases} \xi\text{\_short\_distance}_{vit} & \text{if distance} < 10, \\ \xi\text{\_single\_child}_{vit} & \text{if distance} \geq 10 \text{ and age} < 18, \\ \xi\text{\_single\_adult}_{vit} & \text{if distance} \geq 10 \text{ and } 18 \leq \text{age} \leq 63, \\ \xi\text{\_single\_senior}_{vit} & \text{if distance} \geq 10 \text{ and age} > 63. \end{cases}$$

2. Season ticket: Consideration of monthly tickets per transport association as a daily average.

The fare levels of 59 transport associations are used.

[4] Eisenmann and Kuhnimhof (2017)
[5] Veisten et al. (2024)
[6] Cycling Embassy of Denmark (2019)

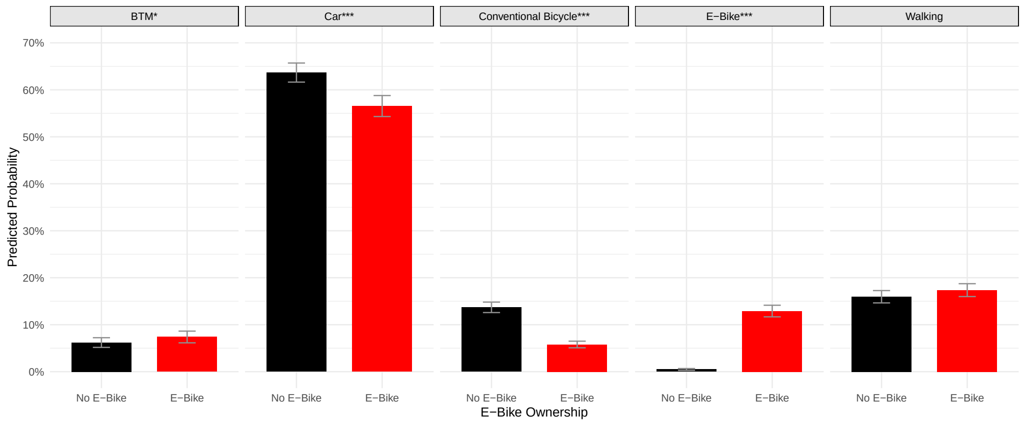
A2. Average Marginal Effects on E-Bike Ownership – “Overall” Dataset

Table A1—: Chi-Squared Tests and Delta Method on the “Overall” Dataset

	χ^2-Tests			Delta-Method		
Outcome	df	χ^2	$P > \chi^2$	dy/dx	Std. Err.	95% Conf. Interval
(1 vs 0) BTM	1	538.72	0.0000	-0.0409	0.0017623	[-0.0443578, -0.0374497]
(1 vs 0) Bicycle	1	1381.57	0.0000	-0.0556	0.0014951	[-0.0585006, -0.0526401]
(1 vs 0) Car	1	116.83	0.0000	-0.0398	0.0036816	[-0.04701, -0.0325784]
(1 vs 0) E-bike	1	4449.35	0.0000	0.1456	0.0021828	[0.1413238, 0.1498804]
(1 vs 0) Walking	1	15.13	0.0001	-0.0093	0.0023994	[-0.0140366, -0.0046309]
Joint	4	5747.98	0.0000			

A3. Predicted Probabilities of Mode Choice – "E-Bike buyer" Dataset

Figure A1. : Average Predicted Probabilities and 95 % Confidence Intervals of Mode Choice from the "E-Bike buyer" Dataset



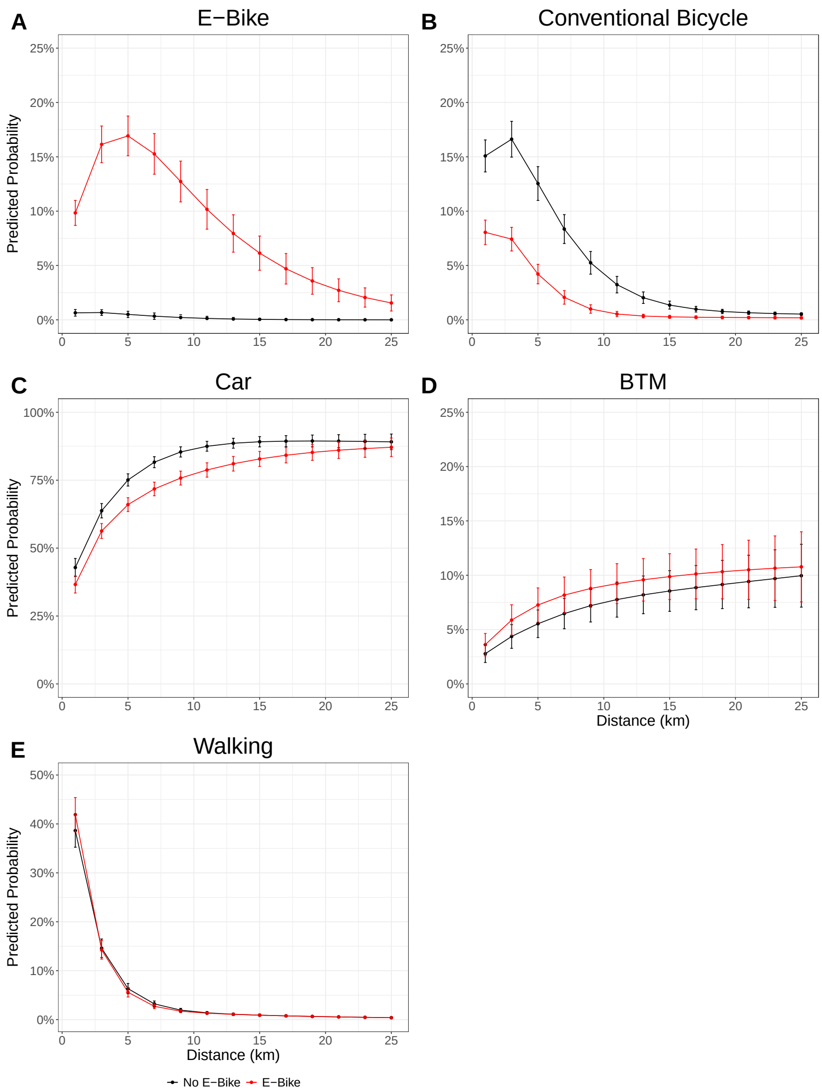
Significant difference between "No E-bike" and "E-Bike" based on Chi-Square Tests. $^{*}p < 0.05$;$^{**}p < 0.01$;$^{***}p < 0.001$

Table A2—: Chi-Squared Tests and Delta Method on the "E-Bike buyer" Dataset

	χ^2-Tests			Delta-Method		
Outcome	df	χ^2	$P > \chi^2$	dy/dx	Std. Err.	95% Conf. Interval
(1 vs 0) BTM	1	3.93	0.0473	0.0119559	0.0060284	[0.0001405, 0.0237713]
(1 vs 0) Bicycle	1	132.65	0.0000	-0.0763596	0.0066298	[-0.0893539, -0.0633653]
(1 vs 0) Car	1	53.26	0.0000	-0.0739972	0.0101399	[-0.0938710, -0.0541234]
(1 vs 0) E-bike	1	360.28	0.0000	0.1244921	0.0065587	[0.1116372, 0.1373470]
(1 vs 0) Walking	1	3.59	0.0580	0.0139088	0.0073365	[-0.0004705, 0.0282882]
Joint	4	445.77	0.0000			

A4. Predicted Probabilities of Mode Choice by Distance from the "E-Bike buyer" Dataset

Figure A2. : Predicted Probabilities and 95 % Confidence Intervals of Mode Choice by Distance from the "E-Bike buyer" Dataset



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