Erasmus School of Economics

Commuter modal choice: determinants & potential substitution

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The views stated in this thesis are those of the author and not necessarily those of the supervisor, second assessor, Erasmus School of Economics, Erasmus University Rotterdam, or the company providing the data.

The anonymized data in this study was retrieved with the full consent of the not-for-profit real estate organization – the subject of this study.

Abstract

Daily commuting is predominantly done by car in high-income countries and urban areas, generating diverse externalities. This study contributes to the research on the topic to gain a more comprehensive understanding of the determinants of mode choice and the potential, thereof, for shifting to more sustainable and active mode choices. This research uses all commuting travel movements of employees working in a real estate not-for-profit company located in the Netherlands during a period of six months. The empirical analysis suggests that the number of modes considered by the individual is the primary determinant for mode choice, followed by secondary factors such as distance, and population density. Finally, while it is found that a substantial number of employees could use an e-bike instead of a car, the overall potential reduction in kilometers of car commute at the company level is marginal.

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1. Introduction

Daily commuting is currently predominantly done by car in high-income countries, including in urban settings where space is limited. Given their increasing size and energy requirements, cars are responsible for many externalities from air pollution – one of the leading causes of premature deaths (Vohra, et al., 2021), to unnecessary accidents, frustration from slow traffic, to economic productivity loss, among others (Santos, et al., 2010). Despite these tangible externalities, commuting behavior has proven difficult to change. Public policy is politically very sensitive or expensive with effects often marginal or with unintended consequences.

Most quantitative studies on commuting mode choice focus on a small (representative) sample of a large population, while focusing on one type of type determinant (e.g. utilitarian, psychological, socio-economic, external environment) and a single mode choice. Therefore, while there is plenty of literature on which determinants have an impact, academic reviews on the topic highlight a lack of comprehensive research on this subject resulting in an imprecise understanding of the effects of the determinants on mode choice (Heinen, et al., 2010); (Javaid, et al., 2020).

The purpose of this research is to provide further insights into decreasing the number of car commuters in urban settings given the associated externalities generated. In a country like the Netherlands where cycling infrastructure is the norm, e-bikes are a viable and healthy alternative to the car for short distances, while highly mitigating externalities.

In this study, population data of a specific group is available. The main advantage of this method is that results are more precise, providing data is accurate. The data used in this research stems from the business-related travel movements for a period of six months from the employees of a not-for-profit association that provides social housing (to be referred to as NPO). The data was collected through an app designed and managed by Mobility Concept B.V., which provides mobility solutions and consultancy to companies throughout the Netherlands. Drawing from previous research on determinants, the central research question of this study revolves around identifying the key factors influencing mode choice among employees at the NPO.

The main data source for the analysis is longitudinal about daily commuting habits of all employees working at the NPO.

This research starts with a literature review of the deterministic factors of commuter choice, followed by an investigation into the dataset that provides an understanding of the group and its traveling habits. Then, the dataset is further analyzed to determine which factors best explain the most frequent commuting choice at the NPO using a multinomial logit model.

The Netherlands possesses widely accessible biking infrastructure, and the second part of this research aims to provide more tangible recommendations to the NPO to decrease the share of commuters using their cars in favor of mode choices generating less externalities e.g. e-bikes.

Hence, the secondary research question arises: what is the substitution potential of the car for e-bikes within the context of this NPO?

Therefore, an estimation of the potential substitution of car commuting for e-bike commuting is subsequently developed. Finally, the discussion puts the results into perspective and provides paths forward to decrease externalities associated with current commuting patterns at the NPO and beyond.

2. Literature Review

2.1 Overview

The literature on transport economics initially attempted to explain modal choice with deterministic or tangible factors such as cost, time, and demographic factors in the 1970s. As it became apparent that these traditional factors only partially explained behavioral choices, different empirical strategies have recently complemented the classic determinants by adding sociopsychological factors and multifactorial approaches (Bretones & Marquet, 2022). According to a representative survey conducted by the Directorate-General for Mobility and Transport of the European Commission, the four main determinants in the Netherlands were considered speed (55%), comfort (45%), pleasure (35%), and environmental concern (26%) (Kantar, 2020), since commuting *costs* in the Netherlands are generally reimbursed. This poll appears to confirm that both determinant/functional factors (i.e., speed & comfort) and non-determinant/non-functional factors (i.e., pleasure and environmental concern) are relevant in explaining commuter behavior. While the factors available in the analysis are limited, this literature review on the factors provides insightful background to support the understanding of the results within this study.

2.2 Main recurring factors

2.2.1 Functional factors

Travel time & distance

Travel time and distance are one of the most important factors for commuting choice. While it is generally accepted that commuters try to minimize their commuting time (Stutzer & Frey, 2008), empirical evidence also suggests that *attitudes* toward the time spent traveling are heterogeneous (Mokhtarian & Salomon, 2001). This heterogeneity can partially be explained by diverging *perceptions* of time, varying on the mode itself and personal characteristics (Wardman, 2004). Further, travel time (for the same trip) may be subject to variability and research suggests that commuters associate value with travel time *reliability*, even if it may take longer (Carrion & Levinson, 2012). Hence, while time (and associated distance) is a simple factor that must be minimized, it is directly affected by other less tangible factors.

Cost

Cost is a classical and important factor in economics for commuting, depending on what and when the commuting is reimbursed by the employer. While cost, on average, is expected to be significantly less important than travel time for commuting (Frank, et al., 2008), the importance of cost generally depends on the income of commuters, with low-income commuters being more price-sensitive (Glaeser, et al., 2008). Financial incentives and reimbursements by the employer that affect the overall cost also seem to have a significant impact on modal choice. A reimbursement for one travel mode increases the probability of using this mode (and decreases the probability of including other modes of transport).

However, providing a reimbursement for bicycles also increases the inclusion of using local (public) transit, likely because they are considered complements (Ton, et al., 2020).

Accessibility

Accessibility refers to “the extent to which land-use and transport systems enable (groups of) individuals to reach activities or destinations by means of a (combination of) transport mode(s), the ability to choose between different transport modes for commuting” (Geurs & Wee, 2004, p. 128). The availability of transport options such as the proximity of the workplace or household to public transport stops, bike lanes, or the availability of parking can all have an impact on mode choice. A study in Portland, USA found that free parking at the workplace significantly increased the likelihood of driving alone, relative to using public transit (Hess, 2001). Further, studies in Canadian cities show that increasing the accessibility of public transport is expected to increase public transport ridership, with low-income households most sensitive to this increase (Cui, et al., 2020). Recent research, especially in the Netherlands, has shown the importance of integrating urban and transport planning with accessibility to shift modal choice away from cars (Bertolini, et al., 2005); (Geurs, 2018); (Pritchard, et al., 2019). To increase the number of cyclists, there is strong evidence that increasing access to dedicated infrastructure is an effective tool (Heinen, et al., 2017). For example, the effectiveness of bike lanes to encourage cycling has been strongly observed during the pandemic (Kraus & Koch, 2021). Accessibility is highly intertwined with the *built environment.*

The built environment

The built environment refers to the way cities and urban space are designed, which impacts the accessibility of different transport systems to commuters, however, a comprehensive causal link has remained difficult to conclude (Handy, et al., 2002). In the United States, “smart growth” is a concept aimed at countering the externalities associated with sprawling, which emphasizes building denser, with mixed land use, and with a pedestrian-oriented design (Cervero & Kockelman, 1997). Indeed, commuters located in more densely populated areas are less likely to use the car (Chen, et al., 2008). However, a meta-analysis aimed at quantifying how the built environment itself has an impact on travel behavior remains inconclusive as evidence shows that the “access” to different destinations according to the mode choice plays a more significant role (Ewin & Cervero, 2010).

Socio-demographic factors

Socio-demographic factors such as age, gender, income, household type, etc. have traditionally been studied in economics. A study investigating the modal shift in San Francisco between 2000 and 2012 shows that individuals with median household income living in a single-family home were most likely to be car-dependent whereas individuals of the lowest average annual household income are least likely to be car-independent (also due to a lack of availability) (Vij, et al., 2017). A study in Pisa found that younger people are more likely to use active modes of transport such as cycling or simply walking (Calastri, et al., 2019). However, recent research conducted by Ton et al. (2020) using the Dutch mobility panel found instead that individuals over 50 were more likely to use active modes of transport to commute. Further, a high level of education was correlated with a higher use of bicycles and trains. Meanwhile, household income did not appear to play a role in mode choice (perhaps since commuting is generally reimbursed in the Netherlands), instead, the type of reimbursement did have a significant impact. Individuals in a larger household were more likely to be car-dependent, especially with children aged under 12. Finally, ownership or having a subscription increases the probability of using the respective mode of transport and negatively increases the probability of using another mode of transport, therefore, creating a substitution effect.

Work-related factors

The workplace is another important modal choice determinant. Ton et al. (2020) show that working full-time decreases the probability of using the bicycle. Oppositely, when the workplace provides facilities such as the presence of bicycle storage, having access to clothes changing facilities and showers are all expected to the probability of commuters choosing to cycle (Heinen, et al., 2012).

2.2.2 Non-functional factors

Convenience and comfort

This determinant refers to the level of enjoyment or travel experience when choosing a transport mode. While it can be debated if this factor is functional, I refer to the methodology used by Bretones & Marquet (2022). It is slightly more difficult to measure as it is more based on perceptions, personal preferences and subject to individual biases, however, a representative survey has shown that this is one of the most important factors for Dutch commuters (Kantar, 2020), therefore, it is of high relevance. Further, “enjoyment”, together with health are the two main reasons for commuters to substitute e-bikes with their cars (Plazier, et al., 2017).

Habits

The importance of past or present habits must not be underestimated, research has shown that people’s daily traveling habits tend to be sticky and most people consider only one or 2 modes for all types of daily trips (Ton, et al., 2020). Therefore, people appear to make a rational choice based on the (imperfect) information available at a specific point in time and create a habit that may or may not be in their best interest over time. Based on this, to counter the bias of habits, Esztergár-Kiss, et al. (2021) investigated if a personalized route planner based on participants’ preferences for travel time, cost, environmental effect, and health effect could change individual habits. The results were disappointing as the personal route was accepted less than half of the time[1]. Perhaps, this shows how sticky habits are. After all, it has been long established in business that the cost of acquiring a new client is manyfold the cost of retaining an existing one (Gallo, 2014).

[1] It must be considered that some suggestions in the research, like taking the bike or car may have been unrealistic for some participants.

Social and personal norms

"A norm exists in a given social setting to the extent that individuals usually act in a certain way and are often punished when not seen to be acting in that way" (Axelrod, 1986, p. 1097). In other words, the social setting in which a commuter identifies most strongly has an impact on the travel mode chosen by the individual. Adopting a different behavior would be of considerable social cost to the individual. For example, members of an e-bike association may perceive a strong social norm to commute daily with an e-bike even if the built environment is poor and the distance is high.

Recent evidence suggests that personal norms (also known as internal norms) may also have a substantial impact on commuter mode choice (Ababio-Donkor, et al., 2020). This specific study focused on the commuting behavior of individuals with pro-environmental attitudes in Edinburgh, UK. Environmental awareness was also found to be the most important non-functional factor in electric micro-mobility (Bretones & Marquet, 2022).

Attitudes and personality traits

Attitudes and personality traits, sometimes referred to as individual-specific variables may help to explain diversity in commuting behaviors that cannot be explained by factors introduced above or in the wider literature. For example, understanding why two neighbors commuting to the same office choose different travel modes. These individual-specific characteristics are difficult to quantify. Nonetheless, Johansson, et al., (2006) partially account for this challenge by combining the individual significance of environmental preference, safety, comfort, convenience, and flexibility.

2.3 Synthesis

This above overview shows that mapping commuter behavior choice is a complex task that requires precise microdata. Up to September 2023, no study published has considered all of these factors when studying commuter behavior because data was unavailable. At the same time, gaining such a high level of information on individuals does raise privacy and ethical questions even if insights are treated with utmost respect and care. In this study, only functional factors are available for consideration. If the non-functional factors do have an impact on the population, then one should expect a significant part of the model to remain unexplained. These other factors must be considered and brought when reflecting on the impact of results from this study and future research.

3. Methodology

3.1 Data collection

The main data source for the analysis is longitudinal about daily commuting habits of all employees working at the NPO, a not-for-profit organization whose mission is to provide affordable housing in the Netherlands. The data is collected through an app designed and managed by Mobility Concept B.V., which provides mobility solutions and consultancy to companies throughout the Netherlands.

The data was collected between November 1st 2022 and April 30th 2023 and records all work-related movements by employees. Commuters record their movements on the app, on which it is possible to directly buy public transport tickets. In terms of compliance, the employees are incentivized to use the system, since they get compensated or reimbursed for commuting (see Table 1). At the same time, potential fraud is prevented by random checks and disciplinary consequences. While human error can never be excluded (and evidence thereof was found), data quality is sufficiently ensured.

Table 1: NPO compensation system per mode choice

Modal choice	Compensation system
Car, motorcycle, scooter/moped	€ 0,19 per kilometer net, up to 80 kilometers
Cycling, walking	€ 0,19 per kilometer net + € 0,11 per kilometer gross, up to 80 kilometers
Public transport (incl. bus, tram, metro, railway)	2nd Class travel is fully reimbursed 1st Class travel possible but only 2nd class equivalent is reimbursed
Working from home	€ 2 per day

In addition, to account for the possibility that accessibility to the office may be playing a role in transport choice, the distance of public transport was investigated. Train stations were found by searching the nearest train station next to the office and looking at the walking distance to it. Then, considering that most offices are located over 10 minutes by foot, the same method was applied to the nearest bus, tram, or metro stop (see Table 2).

Table 2: NPO offices overview

City office	Address	Train station	Metro/tram/bus	Number of employees
Weest	Van Houten Industriepark, 1381	16 mins; 1.3 km	1 mins; 0.01 km	10
Haarlem	Jetty Velustraat, 2033MX	32 mins; 2.5 km	3 mins; 0.3 km	33
Haarlemmermeer	Burgemeester Pabstlaan, 2131XE	126 mins; 10.2 km	2 mins; 0.15 km	38
Almere	Rentmeesterstraat, 1315JS	4 mins, 0.28 km	4 mins; 0.28 km	23
Amsterdam-West	Anderlechtlaan, 1066HL	39 mins; 3.1 km	2 mins; 0.2 km	94
Amsterdam-Oost	Muiderstraatweg, 1111PS	13 mins; 1.0 km	2 mins; 0.2 km	241
Amsterdam-Noord	Floraweg, 1032 ZG	38 mins; 3.1 km	1 mins; 0.1 km	36
Pakhuys Afrika	Jollemanhof, 1019GW	23 mins; 1.8 km	1 mins; 0.08 km	487

nb:10 employees do not indicate a specific office location

Further, rural areas where population density is lower tend to receive lower coverage of public transport, which restricts the choice of transport of commuters (Limtanakool, et al., 2006). To account for this, the home city[2] of each commuter was matched by the 2022 population density of each municipality, and district, using the Dutch Central Bureau of Statistics data (CBS, 2023). For simplicity, municipalities and districts that have less than five hundred inhabitants per square kilometer were considered rural, and those with five hundred square kilometers or more were considered urban. A minority of employees' (116) home cities did not match any result with CBS. After scrupulous checks, the following locations "Zaandam", "Den Haag", "Bussum", "Santpoort-Noord", and "Velserbroek" were considered urban. And "Heerhugowaard" was considered rural, while the rest (69 instances) were left unmatched.

Another potentially important indicator of mode choice is the *distance* because a higher distance is expected to decrease the likelihood of using a bicycle, walking, or using a scooter. The distance was calculated by using the coordinates of the city and the address of the office address. With this information, the shortest spatial was calculated. Therefore, the distance remains very approximate but does provide a relative indication of who commutes from within or a nearby city or a different part of the country. This can be useful to determine the substitutability of transportation modes.

3.2 Description of variables

The variables included in this analysis are equivalent to some of the variables introduced in the literature review. *Year of birth* partially reflects one of the socio-demographic components, it was found that individuals aged over 50 were more likely to use active transport modes (Ton et al., 2020).

[2] Data is imperfect and the Home City was sometimes recorded as an actual city and sometimes as a district. Therefore, the "home city" was matched to the district level in 2022 CBS dataset, which also includes cities.

Distance was linked to the factor of travel and distance, while one does not have the travel time which is expected to be a more precise indicator than distance, this does an adequate picture as long as commuters travel increases proportionally to the distance. Of course, the perception of time itself may be subject to the comfort of travel. Longer distances are expected to decrease the use of the bike due to physical reasons and local transit (given that is designed for small distances).

The *commuting frequency* provides information on how often a commuter reports going to work during the period analyzed. While it does not account for how often employees work from home, a higher commuting frequency is associated with a higher probability of working more (hours). Employees who work full-time are less likely to use the bicycle (Ton et al., 2020).

Population density is considered to be a good indicator of the built environment in the Netherlands, whereby a higher population density is expected to decrease the use of the car (Chen, et al., 2008).

Multiple modes indicates the traveling habit of commuters, past evidence suggests that most individuals can consider up to two transport modes for all types of daily trips (Ton et al., 2020).

Distance rail station and *distance local station* aim to provide a more precise understanding of the accessibility of public transport to commuters. Of course, a smaller distance is expected to make a mode more accessible and, hence, more attractive. However, given the lack of variability in the distances to the office, the results may not be very conclusive.

The *mobility category* takes the value of 1 when employees are considered to have a high level of business travel movement, else 0. Concretely, these are mainly employees who spend a significant amount of time visiting apartment buildings for rental reasons. They are selected by the board and provided €300 as compensation for using their own travel arrangements. It is unclear what the effect of this policy is given that it simply provides more financial support without encouraging the use of a specific mode. It is also questionable if this policy is linked to another factor introduced in the literature review and could be considered a cost or a work-related factor.

Table 3: Overview of variables

Variable	Type	Description	Literature review
Choice	Dependent	Categorical variable indicating the most frequent mode choice chosen over the time period. It can take the following values: “Car, motorcycle”, “Cycling, walking”, “Bus, tram, metro”, “NS – 2nd class”, “Moped”, “Undisclosed”	-
Year of birth	Independent	Variable indicating the year of birth of the employee.	Socio-demographic – functional
Distance	Independent	Continuous variable denoting a straight-line distance between the coordinates of the city of residence of the employee the coordinates of the office location in kilometers.	Travel & distance – functional
Commuting frequency	Independent	Discrete variable indicating the number of registered trips of the employee on the Mobility Concept app between November 1st 2022 and April 30th 2023.	Work-related factors – functional
Population density	Independent	Discrete variable indicating the population density of the city where the employee lives.	The built environment – functional
Multiple modes	Independent	Discrete variable denoting the number of different modes chosen by the employee.	Habits – non-functional
Distance rail station	Control	Discrete variable denoting the distance between the office and the nearest rail station in kilometers.	Accessibility – functional
Distance local station	Control	Discrete variable denoting the distance between the office and the nearest bus, tram, or metro station in kilometers.	Accessibility – functional
Mobility Category	Control	Dummy variable indicating the value 1, if the employee has a special mobility budget of 300 euros, and 0 if the employee is assigned to the standard mobility policy.	Other

3.3 Model structures for regression estimation

The first part of this research investigates which functional factors are most associated with the most frequently chosen mode *choice*, a categorical variable. The established way to aggregate individual travel behavior is through a discrete choice analysis, which is based on random utility theory (Ben-Akiva & Bierlaire, 2003). The underlying logic in this research is that the individual n's most frequently chosen choice *i* within choice set *C* over the time-period of six months corresponds to the individual's highest deterministic utility V_{in}. In this model, the decision-maker is assumed to have incomplete information, which creates a source of uncertainty ε_{in}. In sum, they represent the individual's (n) utility function (U) for the preferred mode choice *i*. This approach is followed in this research, whereby, the following utility function is assumed with individual n associates with the experienced choice *i*. X_{in} represents the set of independent and control variables, and e_{ij} is the random error term.

Equation 1: Utility function (Ben-Akiva & Bierlaire, 2003, p. 11)

$$U_{in} = V_{in} + \varepsilon_{in} = X_{in}\beta + e_{in}$$

The most widely used estimators to derive population choice behaviors are conditional logit models, as introduced by McFadden (1973). Essentially, the model estimates the probability of a random individual from the population choosing an alternative i. Given that the dependent variable at hand, "choice", consists of more than two categories, an extension to the model, multinomial logit models (MLN), are necessary. According to Bhat & Koppelman (2003) in the Handbook of Transportation Science, the MNL "model has been the most widely used structure for modeling discrete choices in travel behavior analysis" (p. 46) and they have continued to be widely used as up to more recently, see (Silvestri, et al., 2022); (Ton, et al., 2020); (Islam & Hoque, 2020); (Thrane, 2015); (Bhat & Gossen, 2004).

The model regression is formalized by the probability $P(i|C_n)$ of individual n with characteristics x_i to use the i^{th} category as the most frequent mode choice.

Equation 2: MNL probability function

$$P(i|C_n) = \frac{e^{\beta' n^{x} i}}{\sum_{j \in C_n} e^{\beta' k^{x} j}}$$

A key characteristic of this model is the Independence from Irrelevant Alternatives (IIA) assumption, which implies that all mode choices should be available to everyone (Cheng & Long, 2007). This assumption could be disrupted if an additional mode not accounted for in the data is used by individuals or if not every modal choice is available to everyone. In the present case, it appears unlikely that an additional mode was unaccounted for given all the possible commuting alternatives. The availability of modes to everyone is something that could be debated. While every commuter is able to choose the mode choice it prefers, for example, the lack of ownership of a car could potentially restrict the number of mode choices available. Hence, it is common practice to use complementary models such as the nested logit model, the cross-nested model, or the mixed logit model (Ton, et al., 2020); (Train, 2002); (Bhat & Koppelman, 2003).

More importantly, this study analyses an entire population instead of a population sample. Therefore, the probabilities are, *per se*, representative. Thus, the IIA assumption can be relaxed, as long as the scope of the findings is restricted to the NPO employees only.

The results of the analysis can be found in Table 6. The base outcome (*choice*) is the car or motorcycle—the most prevalent transport choice. The car and the motorcycle are combined since they are not distinguished in the dataset. The first results are the standard multinomial logistic regression analysis, combined with the relative risk ratio (to car users). To gain a more precise understanding of the effect sensitivity, the average marginal effects were also added. One of the challenges was that many employees were missing one or two pieces of information, to allow for the model to run properly, the missing values were changed to the population median, when applicable.

3.4 Car substitution potential

The car substitution potential is an estimation of the potential for car trips to be substituted by e-bikes (or other electric micro-mobility vehicles). It is based on three metrics: the potential number of employees (who could substitute fully or partially their car for a bike or e-bike), the potential number of trips, and the potential number of kilometers. It is important to note that this potential considers what is considered physically possible on average and not the willingness to travel using an e-bike or other factors considered in the previous part. To go about this, I start by estimating the car substitution potential of the company, which is an estimation of the number of employees that could avoid using their cars for some or all of their trips to work.

The idea is to estimate how many trips by car could have been replaced with using an e-bike or similar micromobility solution, during the time-period. Other modal choices are not considered for several reasons. First, since only information about city addresses is analyzed, it is impossible to objectively estimate the accessibility of public transport, and their convenience for every commuter. Further, public transport infrastructure is relatively rigid and companies such as the NPO do not directly influence the future development of the infrastructure. Instead, it is possible to take measures to increase the availability and use of bikes or electric bikes among individuals through different schemes.

The largest physical observable determinant for cycling is the distance. As distance increases above a commuter-specific value, the distance for cycling is considered too high, and alternative modes of transport such as the car or public transport are favored due to the physical effort and limited speed. As the descriptive statistics show in Table 5, the average commuter cycles less than eight kilometers, while the average commuter drives nearly twenty kilometers. Therefore, distance is a simple and an effective proxy to determine the substitution potential of the car.

However, the challenge is to estimate the distance that commuters are willing to use an e-bike or bike or other light electric vehicle for, considering that the maximum distance is individual-specific. In this sense, the distinction is important because e-bikes have been found to increase the maximum tolerated distance because it is generally quicker and reduces the physical effort relative to a regular bike (KiM, 2015); (Cairns et al., 2017). Within this research, I estimate a distance for electric bikes because they are considered the most promising substitute for cars (Haas, et al., 2022); (Kruijf, et al., 2021); (Kroesen, 2017).

Figure 1: Distance distribution of cyclists with the threshold of 15 kilometers

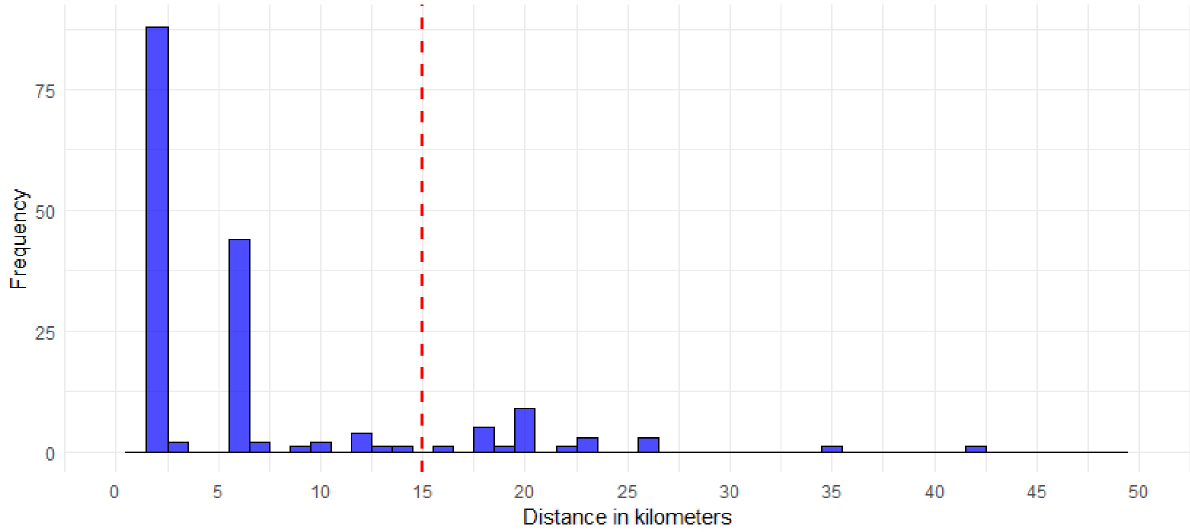


Figure 1 shows that the NPO employees predominantly cycle (or walk) short distances up to six or seven kilometers (3rd quartile is 6.45). This provides a good first indication into up to what distance commuters at the NPO are willing to bike but I also expect it to be a conservative estimate, given that the data does not distinguish between normal bikes and electric bikes. Within an e-cycling program in North Brabant, Kruijf et al. (2021) show that 74% of participants used e-bikes for trips between 10-15 kilometers, 71% of participants used e-bikes for trips between 15-20 kilometers, and 64% used e-bikes for trips of 20+ kilometers, given a compensation ranging between 8-15 cents per kilometer (Kruijf, et al., 2021). Another study estimates that 93% of all e-bike trips in the Netherlands were done within a distance of 15 kilometers, a distance about twice as large as for trips by normal bikes (KiM, 2015). Hence, I estimate in this model that e-bikes may fully or partially substitute the car for distances of up to 15 kilometers.

3.4.1 Potential number of affected employees

The potential number of affected employees denotes all employees who use the car (or motorcycle) most frequently and are reported to live within 15 km of the office. These employees have the potential to substitute the car partially or fully with a normal or e-bike.

3.4.2 Potential number of trips

The potential number of trips is more complex to estimate because one can expect the effective car substitution potential to be commuter-specific – on average, people who have access to an e-bike replace only a part of their trips (Haas, et al., 2022). The number of potential trips saved is highly dependent on the share of trips we assume the employee to replace, which itself depends on individual heterogeneity and the incentives in place. In this analysis, the potential number of trips only considers individuals for whom the car is the most frequent mode of transportation. This narrow scope was chosen because one can expect people who already use their bike most frequently to already be cycling at their full potential.

Therefore, three estimations are created based on different assumptions. The “optimistic” estimation assumes *pure* potential whereby all car trips within 15 kilometers can be replaced by cycling. The “balanced” estimation assumes that the substitution potential is sensitive to distance, with short distances being fully substitutable and longer ones partially substitutable at a rate of 80% (practically, this implies commuters still commute by car once a week). The “pessimistic” estimation assumes that car commuters are attached to their car, and are, on average, never willing to fully substitute the car for a (e-)bicycle. Within the group of car commuters, some are unimodal and others are multimodal, meaning that they may already be occasionally using the bike or public transport. For the latter group, it is assumed that the substitution rate is an aggregate. For example, if we assume that an employee living 12 kilometers away from the office initially undertakes 6 trips by car and 4 trips by bike in a given week. The optimistic estimation technique calculates that all 6 trips by car are be substituted into bike trips, the balanced estimation calculates that 4 of the 6 trips by car are substituted into bike trips (so that 80% of all trips are substituted) and the conservative estimation calculates that none of the car trips are substituted into bike trips (so that 60% of all trips are substituted. For a clearer overview, please refer to Table 4.

Table 4: Substitution rate based on estimation types

Estimation type	Distance in meters	Substitution rate
Optimistic	0 – 15’000	100%
Balanced	0 – 5’000	100%
	5’001 – 10’000	90%
	10’001 – 15’000	80%
Conservative	0 – 5’000	80%
	5’001 – 10’000	70%
	10’001 – 15’000	60%

3.4.3 Potential number of kilometers

Equation 3: Potential number of kilometers

$$Number\ of\ kilometers = \sum (number\ of\ trips\ substituted * Distance\ /1000)$$

The potential number of kilometers depends on the potential number of trips that are substituted. This measurement is the aggregate of the product of the distance commuted and the number of commuting trips that have been recorded for each employee (see equation 3). This parameter also incorporates an optimistic, balanced, and conservative estimation.

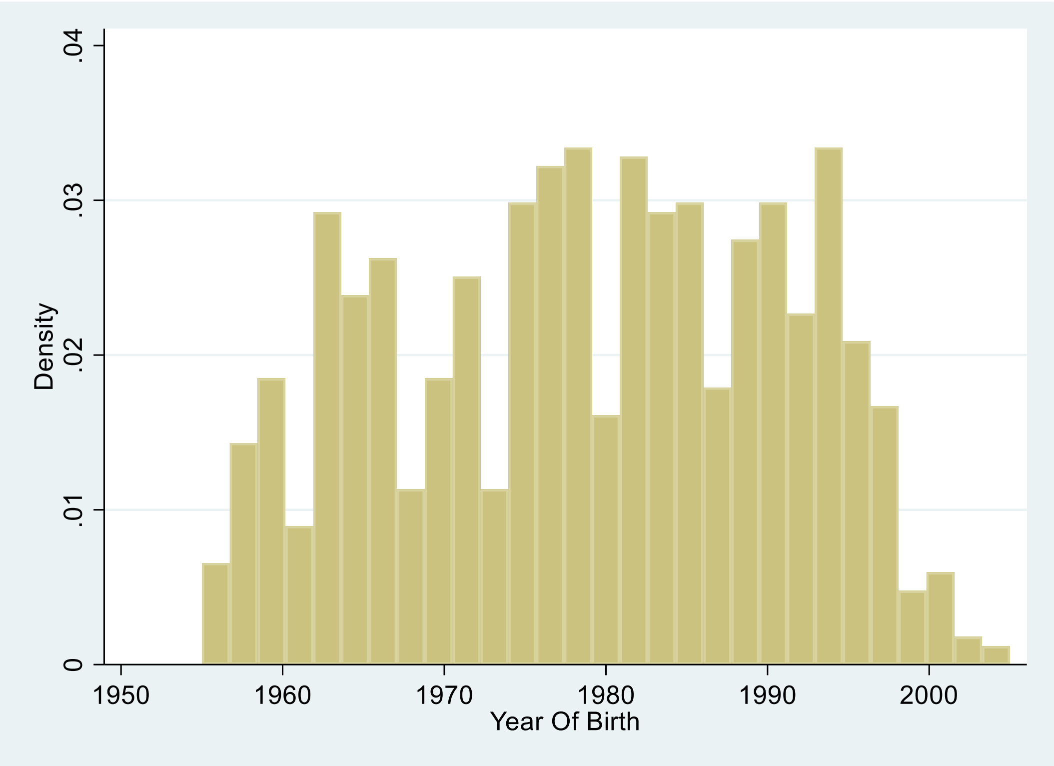
4. Descriptive statistics

The descriptive statistics provide a good overview of the type of population consisting of the employees at the NPO. The relevance of these findings is to provide some background and further understanding of the results that are to be provided in the regression analysis, to eventually bring the results into perspective with the broader Dutch population. For this first part of the analysis, the initial dataset was restructured into count data, with the preferred mode choice defined as the most frequent mode chosen during the 6 months period for each employee on which data was available. The number of recorded trips for each individual employee was aggregated over time. The distance is the approximate measure in meters between the recorded home city and the registered office. In addition, the number of different modes for commuting purposes was recorded for each employee during the time period.

4.1 Employee demographics

The dataset consists of 972 employees, which can be considered as the population of the company. The employees are generationally a mixed group as illustrated in (see Figure 2), with the mean year of birth being 1979 and a low standard deviation. As the company is based in and the surroundings of Amsterdam, about a third of employees live in Amsterdam itself. The data also shows that about 2/3 of employees are located in ten cities (excl. 10 commuters for which information is unavailable) mainly in the suburbs of Amsterdam. Table 2 shows that the NPO consists of 2 main offices where nearly 75% of employees work, the remaining spread in six smaller offices.

Figure 2: The NPO age distribution



4.2 Preferred Modal choice

The mode choice being our variable of interest, I start by grouping the 972 employees by their preferred mode choice and whether they live in urban areas (see Table 5).

The preferred modal choice “Undisclosed” refers to employees for whom no travel data was registered. This can be due to an unwillingness to use the service by Mobility Concept or because the employee did not work during the time period. The data provides clear evidence that the preferred modal choice for the NPO employees is the car or the motorcycle with nearly 55% of the employees (which is conservative considering some employees do not disclose their traveling behavior) making the most trips using one of these 2 transport modes. The scooter and NS 2nd Class transport modes were the least popular modes of transport with only a fraction of employees using them. For NS 2nd, it must be considered that this may be slightly underrepresented. This is due to the data collection process for which if a commuter uses local transit to the local train station, and local transit from the train station to the office, the commuter’s preferred mode choice is considered “Bus, tram, metro” even if the majority of the distance may have been operated by NS.

4.3.1 Urban and rural location

Table 5 provides data on commuter travel behavior based on whether they live in urban (density of 500 inhabitants/km^2 or more) or rural areas (less than 500 inhabitants/km^2). This distinction is important because past research has shown how people living in rural areas may have less accessibility to public transport than those living in rural areas (Limtanakool, et al., 2006). The data suggests that over 90% of the NPO employees live in urban areas.

The rural commuters almost entirely commute by car and live on average over 50 kilometers away from their workplace. Further, the average year of birth of car commuters living in rural areas is the second lowest in the dataset together, perhaps indicating a visible trend to retreat in the countryside as one grows older.

4.3.2 Year of birth

When it comes to the year of birth and preferred mode choice, the descriptive statistics do not suggest a clear generational change between preferred modal choices. Nonetheless, it is worth noting that commuters using local transit are, on average, four years younger than those using the bicycle or walking.

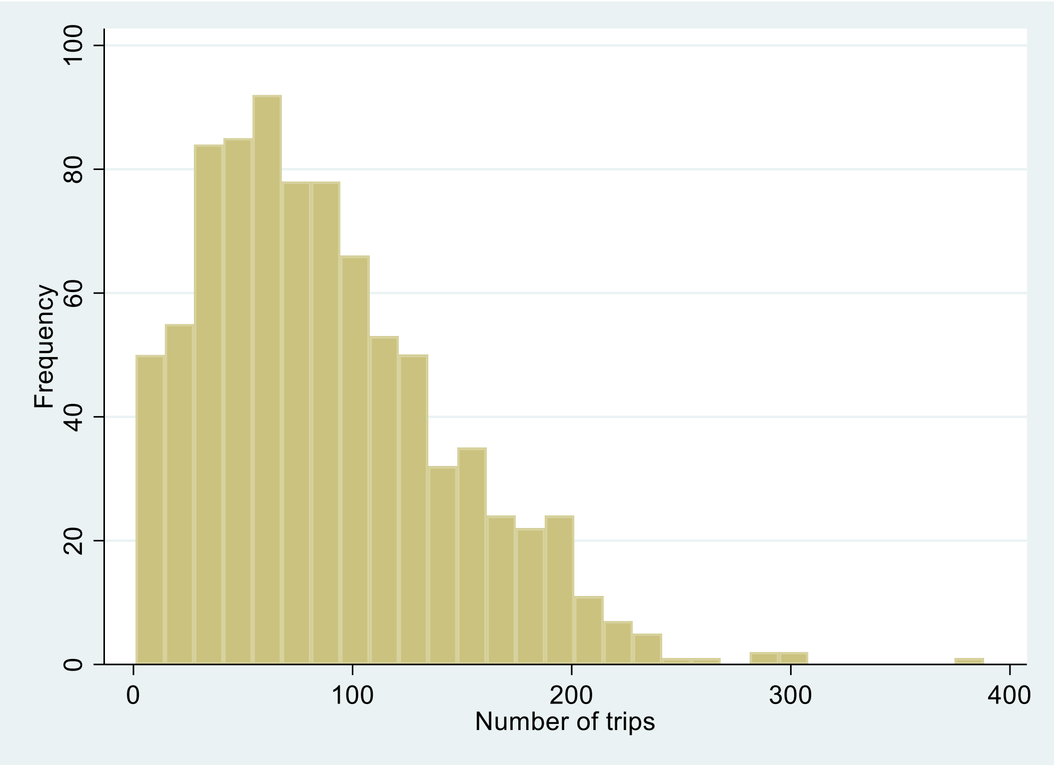
4.3.3 Distance to work

For the average distance between the office location and the home city of the employee, the data suggests some large differences in commuting distances. One sees that those commuting by rail live the furthest away from home with an average of over 30 kilometers. As could be expected, those preferring the bike, walking, or using a private scooter live on average the nearest to their workplace. To build on the previous section, it must also be highlighted that the average distance by local transit is about 15.5 kilometers, whereas the average distance for those using the bicycle is about eight kilometers. Hence, perhaps the difference in the year of birth relative to commuting choice could stem from the distance more than the year of birth. For more information on this, please refer to section 5.

4.3.4 Commuting frequency

On average, employees recorded nearly 88 commuting trips during the 125 working days of this period, which corresponds to going about 1/3 of the time to the office. Please refer to Figure 3 for the commuting frequency distribution. This may seem like a relatively low number but a plausible one given the substantial variation among employees (indicated by a high standard deviation), which is comprehensible given the possibility to work remotely and part-time. One does see some notable variance between the groups with those commuting by local transit (bus, tram, metro) recording the most trips and those transiting with NS doing the least number of trips. The fact that we see more trips done by local transit is unsurprising given that a transfer may be recorded as two different trips depending on how the user recorded the movement in the app. It can also be observed that the average number of trips is over 15% lower than for individuals living in urban areas. This could, in part, be due to that people living in rural areas live on average three times further away from the office than those living in urban areas, most likely resulting in higher commuting time, especially given that working from home has become an alternative (see Table 5).

Figure 3: The frequency in the number of commuting trips



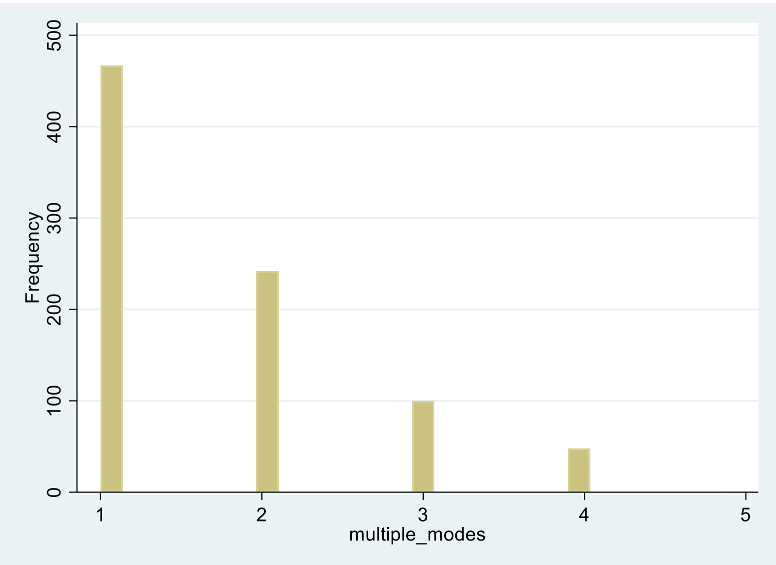
4.3.5 Population density

The average population density for the NPO commuters is very high at over 3000 inhabitants/km^2 but with a standard deviation of over 2000. Overall, the descriptive statistics on average population density clearly indicate that commuters preferring to cycle, walk, or scooter to work live in densely populated areas, whereas those preferring to use the long-distance rail or the car are more likely to live in less populated areas. However, the large standard deviation for most of the modal choices indicates a large level of individual heterogeneity. Further, it must be considered that the office locations are also located in urban areas, so that commuters living close to the office are, by definition of the parameter, living in more urban areas. Therefore, it cannot be distinguished from the data if this correlation between population density and mode choice could also be linked to the proximity to the office.

4.3.6 Number of modes used

The mean number of modes represents how many modes, on average, were chosen at least once by each employee during the time period, given a preferred commuting choice. This parameter provides insights into the commuting mix of commuters, which could provide some insights into the substitution potential of other modes. If the commuter considers a specific mode choice, then it is subject to use it on a regular basis. The employee data shows that the average number of modes considered is 1.69, which implies that employees have a small choice set, similar to previous findings in the Netherlands (Ton, et al., 2020). In fact, Figure 4 shows that about half of employees only consider a single mode in their commuting mix.

Figure 4: The spread of modes considered during the time period



Further, the data also indicates that NS users are most likely to consider different modes of transport, which is likely due to transfers to local transit or perhaps the use of the car or other modes on certain days. Indeed, the NPO offices are over 10 minutes' walk from a train station (except the one in Almere).

The commuters who prefer to use the car are least likely to consider or combine it with other modes of transportation. Figures 5 and 6 provide a clearer illustration of the low number of modes considered by commuters, especially when the car is the preferred mode choice of the employees.

Figure 5: The spread of modes considered by cyclists

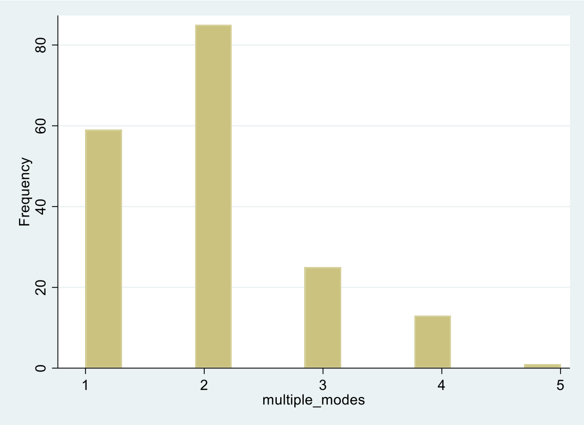
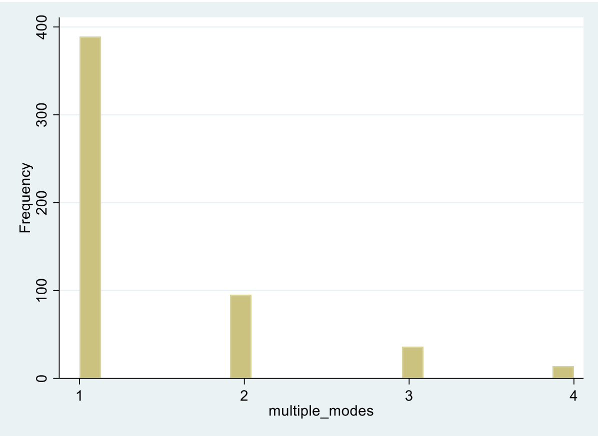


Figure 6: The spread of modes considered by car commuters



4.3.7 Distance rail station

One of the key factors impacting modal choice is accessibility. This factor measures the distance of a rail station to the employee's office by using the shortest distance by foot on Google Maps. One can expect a smaller distance to the rail station to increase its accessibility, therefore, its likelihood to be the most frequently used by employees and *vice versa* for a longer distance. However, this parameter does not consider the accessibility of the commuter's home to the train station, expected to be equally important. Besides, even if it is technically considered a numerical variable for analytical purposes, this variable can only take eight values (since there are 8 locations). Due to these considerations, while a weak correlation is expected, this parameter's potential effect is expected to remain weak and imprecise.

The results from Table 5 show that the average distance of a train station is 2.09 kilometers, equivalent to a bit more than 20 minutes of walking at a standard pace. One sees that those preferring the NS service are located on average slightly lower distance of about 1.87 kilometers by foot from the office.

A closer look at the preferred modal choice by office also provides a mixed picture with only a single employee preferring the train at the office in Almere where the rail station is a few minutes away. Instead, the highest ratio of commuters preferring the rail (6.98%) is at the headquarters of Jollemanhof, located 1.8 kilometers from Amsterdam Centraal. Nonetheless, the office is located next to a local tram stop with a direct link to the train station.

4.3.8 Distance local transit station

The distance to the local transit station is calculated in the same way as the distance to the rail station but by investigating a bus, tram, or metro stop (all three options are weighted equally). As shown in Table 2, all offices are much more easily accessible to local transit with a range between 10 and 200 meters by walking distance, and an average of 130 meters. It could be questioned if commuters mind or notice such a small difference in distance. In fact, commuters preferring to use local transit such as the metro, bus, or tram are on average the furthest group from a local transit stop.

4.4 Synthesis

To summarize, the NPO employees are established individuals who are forty-four years old on average (though the age group is quite diverse). They usually don’t live close to the office but in a nearby city located on average just above 15 kilometers away from work. To avoid commuting, they enjoy working from home (or working part-time). When they do commute, they mainly use the car to work, and sometimes the bicycle but they generally avoid public transport. Perhaps, they shy away from taking the train because most train stations are not very accessible from the office.

Table 5:Summary of the descriptive statistics

	Employee count	Avg year of birth	Avg distance	Avg commuting frequency	Avg population density	Avg number of modes	Avg distance rail station	Avg distance local transit station
NS – 2nd class	**48**	**1979**	**31’853**	**68**	**2476**	**2.71**	**1.87**	**0.11**
	4.94%	***12***	***18’959***	***45***	***1716***	***0.87***	***1.32***	***0.06***
Rural	3	1981	68’994	54	322	3.33	1.27	0.16
	0.31%	*11*	*44’146*	*18*	*26*	*0.94*	*0.38*	*0.06*
Urban	42	1980	29’241	68	2689	2.69	1.92	0.11
	4.32%	*12*	*11’126*	*46*	*1644*	*0.86*	*1.40*	*0.06*
Undisclosed	3	1970	19’688	88	-	2.33	1.80	0.08
	0.31%	*11*	-	*36*	-	*0.47*	*0.00*	*0.00*
Bus, tram, metro	**84**	**1981**	**15’568**	**114**	**3766**	**2.32**	**2.28**	**0.15**
	8.64%	***11***	***14’724***	***83***	***1859***	***0.88***	***2.15***	***0.07***
Rural	1	1986	-	174	273	2.00	1.80	0.08
	0.10%	-	-	-	-	-	-	-
Urban	78	1981	14’672	115	3907	2.32	2.30	0.15
	8.02%	*11*	*13’458*	*85*	*1746*	*0.88*	*2.21*	*0.07*
Undisclosed	5	1990	50’521	89	-	2.40	2.10	0.19
	0.51%	*7*	*18’870*	*45*	-	*0.80*	*0.78*	*0.08*
Bicycle, walking	**183**	**1977**	**7’831**	**90**	**4643**	**1.97**	**1.88**	**0.12**
	18.83%	***12***	***12’755***	***53***	***1526***	***0.89***	***1.05***	***0.07***
Rural	1	1998	62’533	21	377	4.00	1.80	0.08
	0.10%	-	-	-	-	-	-	-
Urban	172	1977	7’500	90	4749	1.92	1.86	0.12
	17.70%	*12*	*12’200*	*52*	*1375*	*0.85*	*1.07*	*0.06*
Undisclosed	10	1979	8’469	91	-	2.60	2.08	0.10
	1.03%	*11*	*1’697*	*54*	-	*1.11*	*0.58*	*0.07*
Car, motorcycle	**534**	**1979**	**19’427**	**85**	**2567**	**1.39**	**2.16**	**0.14**
	54.94%	***12***	***16’077***	***52***	***1992***	***0.73***	***2.01***	***0.07***
Rural	41	1977	51’528	74	290	1.71	1.97	0.12
	4.22%	*13*	*25’539*	*43*	*137*	*1.04*	*1.44*	*0.07*
Urban	414	1979	17’706	85	3015	1.38	2.19	0.14
	42.59%	*11*	*14’266*	*53*	*1849*	*0.69*	*2.02*	*0.07*
Undisclosed	79	1981	22’419	90	-	1.28	2.12	0.14
	1.03%	*11*	*1’697*	*54*	-	*1.11*	*0.58*	*0.07*
Scooter	**9**	**1979**	**7’194**	**75**	**4439**	**2.11**	**3.08**	**0.13**
	0.93%	***12***	***6’097***	***60***	***1688***	***0.99***	***2.62***	***0.06***
Urban	9	1979	7’194	75	4439	2.11	3.08	0.13
	0.93%	12	6’097	60	1688	0.99	2.62	0.06
Total	**972**	**1979**	**16’468**	**88**	**3233**	**1.69**	**2.09**	**0.13**
	100.00%	***12***	***16’356***	***56***	***2071***	***0.89***	***1.78***	***0.07***
Undisclosed	114	1978	13’225	-	3835	-	1.97	0.14
	11.73%	*13*	*14’979*	-	*2019*	-	*1.10*	*0.07*

nb: In the first column, the first line is the absolute value, and the second line is the ratio in percentage. In the following columns, the first line is the absolute value (of the average), and the second line is the standard deviation.

5. Results

5.1 Regression results

Table 6 presents the results of the multinomial logit model, as well as the risk ratio of transport mode choice based on the determinants introduced earlier. The base outcome is the car and motorcycle. When data was missing on some employees, the median was used as an assumption for the missing value. While the significance level is technically irrelevant in the results, since the analysis is based on the population (instead of a sample), it is shown here because it does provide some insights on the relative strength of the coefficients relative to one another. Complementarily, the risk ratio was also provided to facilitate a more tangible interpretation of the results. A limitation of Table 6 is that the effects are always displayed relative to the base outcome. To account for this limitation, table 7 displays average marginal effects (AME), which provides the average one-unit change in the probability of choosing a mode choice.

In terms of model fit, the chi-squared test statistic estimates that the variables are jointly significant, at a 1% significance level. Further, the multinomial regression model has a pseudo R-squared at calculated 0.2535, which means that the model provides some explanatory value. However, it also shows that a large part of the mode choice remains unexplained by the parameters provided. This is disappointing but unsurprising given the other known factors that have an impact on mode choice introduced in the literature review.

Table 6: Results of multinomial logistic regression

Multinomial Logistic Regression Results

	Dependent variable: Choice		
	Cycling, walking	NS - 2nd Class	Bus, tram, metro
Year of birth	-0.0216062**	-0.026717*	0.0030834
	(0.008872)	0.0147135	(0.0112413)
	0.9786256	*0.9736368*	*1.003088*
Distance	-0.0609409***	0.018094**	-0.0113136
	(0.0125369)	(0.008032)	(0.0110402)
	0.9408788	*1.018259*	*0.9887502*

Commuting frequency	0.0023367	-0.0065988*	0.0083915***
	(0.0018612)	(0.0037337)	(0.0021334)
	1.002339	*0.9934229*	*1.008427*
Population density	0.0004406***	0.0000851	0.0002775***
	(0.0000662)	(0.0000945)	(.0000755)
	1.000441	*1.000085*	*1.000278*
Multiple modes	0.9762994***	1.449551***	1.230975***
	(0.1263003)	(0.1763537)	(0.1447869)
	2.654614	*4.261203*	*3.424568*
Distance rail station	-0.1738273**	-0.1162304	-0.0257254
	(0.0765133)	(0.1313335)	(0.0650564)
	0.840442	*0.8902701*	*0.9746027*
Distance local station	-4.672418***	-1.940373	2.887302
	(1.571505)	(2.580644)	(1.836433)
	0.0093496	*0.1436503*	*17.94484*
Mobility Category	-0.3932228	-0.1280451	-2.112956***
	(0.2862899)	(0.4816149)	(0.746573)
	0.6748784	*0. 8798137*	*0.1208801*
Constant	39.96459**	47.96782*	-11.91425
	(17.53551)	(29.03353)	(22.22642)
	2.27e+17	*6.79e+20*	*6.69e-06*
Model fit:			
Observations			858
LR chi2(24)			438.41
Prob > chi2			0.0000
Pseudo R2			0.2535
Log-likelihood			-645.57332

base outcome = car, motorcycle
* significant at 10% ** significant at 5%; *** significant at 1%
nb: the first line is the MLN coefficient, the second line is the standard deviation, and the third line is the relative risk ratio (RRR)

Table 7: Results of the average marginal effects

Average marginal effects

	Dependent variable: Choice			
	Cycling, walking	NS - 2nd Class	Bus, tram, metro	Car, motorcycle
Year of birth	-0.0025135**	-0.0009574	0.000967	0.0025039**
	(0.0010385)	(0.0006201)	(0.0008054)	(.0011789)
Distance	-0.0075486***	0.0014914***	0.0005388	0.0055184***
	(0.0014556)	(0.0003633)	(0.0007924)	0.0012997
Commuting frequency	0.0001505	-0.0003697**	0.0006273***	-0.0004081
	(0.0002149)	(0.0001585)	(0.0001498)	(.0002511)
Population density	0. 0000474***	-2.82e-06	9.47e-06*	-0.0000541***
	(7.40e-06)	(3.64e-06)	(5.23e-06)	7.45e-06
Multiple modes	0. 0767026***	0.0440097***	0.0589177***	-0.1796301***
	(0.0123916)	(0.0068769)	(0.0088338)	(0.0124839)
Distance rail station	-0.0199694**	-0.0030654	0.0032296	0.0198052**
	(0.0092072)	(0.0056049)	(0.0047923)	(0.0091423)
Distance local station	-0.6387378 ***	-0.0565623	0.3508768***	0.3444233*
	(0.1822088)	(0.1076083)	(0.1301224)	(0.2017898)
Mobility Category	0.0049927	0.0135305	-0.1501042***	0.131581***
	(0.0371725)	(0.0204607)	(0.0566113)	(0.0481191)
Observations			858	

* significant at 10% ** significant at 5%; *** significant at 1%
nb: the first line is the predicted marginal effect coefficient, the second line is the standard deviation

5.1.1 Year of birth

The year of birth appears to be a significant determinant of modal choice with younger employees less likely to commute by cycling, walking, or commute by NS 2nd Class and preferring local transit or the car. The results are significant at 5% for cycling, and 10% for NS 2nd class, which suggests a strong association between the year of birth and cycling and a smaller one with NS 2nd class commute. In fact, a one-year decrease in age is associated with a decrease of over 2% in the odds of using NS or cycling to work relative to the car or motorcycle, ceteris paribus.

The AME shows that a one-year decrease in age decreases the probability of cycling by 0.25 percentage points, ceteris paribus. The effect is significant at a 5% significance level. The opposite effect is true for the car with a significance level of 5%. For the two other mode choices, the magnitude is insignificantly low.

5.1.2 Distance

The distance in kilometers traveled to work between the city of residence and the office address also appears to be a significant determinant of modal choice for cycling, walking, and NS travel. An additional kilometer is negatively associated with the probability of cycling or walking, relative to using the car, ceteris paribus. The association is significant at a 1% significance level, suggesting a high association. Indeed, a one-kilometer increase in distance decreases the odds of using a bike by nearly 6%, relative to taking the car. Conversely, an additional kilometer is positively associated with the probability of traveling using NS, relative to using the car (or motorcycle), ceteris paribus. The association is significant at a 5% significance level. Regarding local transit, one notices a negative association between this modal choice and distance (relative to using the car) but the association is very ambiguous as the significance level is less than 10%.

The results of the average marginal effects show that distance has a significant effect on modal choice, excluding local transit. The strongest effect is on cycling with a one-kilometer increase in distance decreasing the probability of biking by 0.76 percentage points, ceteris paribus. Conversely, a one-kilometer increase in distance increases the probability of using the car by 0.56 percentage points and 0.15 points for NS 2^{nd} Class transit, ceteris paribus. The effects are significant at a 1% significance level.

5.1.3 Commuting frequency

The analysis for the commuting frequency (or the number of registered trips during the time period) also shows evidence to be associated with some modal choices. Specifically, one additional commuting trip is positively associated with the probability of local transit being the favorite choice, relative to the car, ceteris paribus. The association is significant at a 1% significance level. For NS travelers, one additional trip is negatively associated with the probability of the train being the favorite choice. The association, however, is weak with a 10% significance level only. For cycling, the association is positive but not significant, relative to the car.

The average marginal effects provide evidence that a change in commuting frequency has a weak effect on mode choice. A one-unit increase in commuting frequency decreases the probability of the NS – 2^{nd} Class being the favorite mode choice by 0.03 percentage points and conversely increases local transit to be the favorite mode choice by 0.06 percentage points, ceteris paribus. Both of these effects are statistically significant at a 1% significance level.

5.1.4 Population density

The population density denotes the average number of inhabitants per square kilometer in the city of residence of the employee. The results of the analysis provide evidence of a positive association between population density and the probability of the bike or local transit being the preferred modal choice relative to the car. These two associations are significant at a 1% significance level, suggesting a robust association. For NS transit, the association is also positive but not statistically significant, suggesting a very weak association.

The AME results provide additional evidence that population density is positively associated with the probability of using the bike, and local transit, ceteris paribus. It also provides evidence that population density is negatively associated with using the car, ceteris paribus. The effects are significant but very marginal.

5.1.5 Multiple modes

The variable multiple modes denotes the number of different modes used during the time period by employees, sometimes called “the experienced mode choice set” (see Ton, et al., 2020). The multinomial logit model provides evidence that the use of one additional mode significantly decreases the probability of the car being the favorite mode of the commuter, relative to the three other modes. The associations are all significant at a 1% significance level. This factor is the clearest determinant of the mode choice. More concretely, one additional mode in the experience set increases the odds of cycling, walking to be the preferred mode choice by 2.65-fold, 4.26-fold for NS trains, and 3.42-fold for local transit, relative to the car.

The AME further strengthens the observed effects. The effects are strongest for the car whereby one additional mode of transport decreases the probability of the car being the favorite mode choice by nearly 18 percentage points, ceteris paribus. On the opposite, one additional mode increases the probability of the bike being the favorite mode by 7.7 percentage points, 4.4 percentage points for NS, and 5.9 percentage points for local transit, ceteris paribus.

5.1.6 Distance rail station

The distance to the rail station denotes the number of kilometers between the office and the nearest train station. The results of the analysis suggest that an office located further from a train station significantly increases the probability of the car being the preferred mode choice, relative to all other mode choices. The effect is statistically significant at a 5% significance level for cyclists but not for the two other mode choices. One additional kilometer decreases the odds of the bike being the favorite mode choice by 16%, 11% for NS trains, and 2.5% for local transit, relative to the car.

The AME shows the relatively low magnitude of the effects of the accessibility of a rail station with a one-kilometer increase in distance decreasing the probability of using NS trains by 0.3 percentage points. Surprisingly, the distance to the rail station has stronger effects on cycling and the car being the preferred mode choice.

These results are surprising since one would expect NS train users to be the most sensitive to the rail station distance instead of the bike users. These counter-intuitive results could be explained by the fact that only the distance between the train station and the office is accounted for (excluding the distance between the home address and the nearest train station) and the low number of NS commuters. Alternatively, the distance to the train station could be a general indicator of the connectivity of the office, with a higher distance being a more peripheral office location, thus, making the car more attractive.

5.1.7 Distance local station

The distance to the local station denotes the number of kilometers between the office and the nearest bus, tram, or metro station. A longer distance between the office and the nearest local station (surprisingly) increases the likelihood of local transit being the preferred mode choice, relative to the car. However, the effect is not significant suggesting a weak association. Conversely, a longer distance is negatively associated with cycling and NS commute, relative to the car. One additional kilometer decreases the odds of the bike being the favorite mode choice by 99%, 86% for NS transit, relative to the car. Conversely, the analysis suggests that one additional kilometer increases the odds of using local transit by over 17-fold, relative to the car.

The AME further provides supporting evidence for these questionable results. One additional kilometer increases the probability of preferring local transit by 35 percentage points, ceteris paribus. Further, one additional kilometer increases the probability of preferring the car by 34 percentage points. Oppositely, one additional kilometer decreases the probability of cycling by 64 percentage points. The effects are all significant. at 10% significance level or higher.

These questionable results likely stem from the same limitations as those from the distance to the rail station. In addition, all offices are located within 300 meters of a local station. At such a low distance, the connectivity of the station itself may play a more important role such as the destinations available and the frequency of services. These significant limitations may explain the counter-intuitive results found.

5.1.8 Mobility category

The mobility category is a dummy variable that takes the value 1 if the employee has access to a special mobility budget of 300 euros due to frequent traveling. The analysis provides significant evidence that employees with access to this budget are more likely to consider the car as their preferred mode choice for commuting (excl. business travel), relative to the other mode choices. The effect is significant at a 1% significance level for local transit but not the other mode choices. More specifically, having access to a special mobility budget decreases the odds of the bike being the preferred mode choice by 32.4%, by points, 12 percentage points for NS, and 88 percentage points for local transit, relative to the car. These results underline how sensitive commuter behavior is to company policies relative to employee mobility.

The AME shows that benefitting from the special mobility budget very slightly increases the probability of the bike being the preferred mode choice by 0.5 percentage points and using NS by 1.3 percentage points. These effects are statistically insignificant and show that the mobility category has practically no effect on both mode choices. With regards to local transit and the car, the effect is much larger and significant. The mobility budget decreases the probability of preferring local transit by 15 percentage points and conversely increases the probability of preferring the car by 13 percentage points.

5.1.9 Synthesis

Based on the results at hand, I conclude that the primary determinant for modal choice is the number of modes that is considered by commuters with those who prefer the car most likely considering a single mode of transport and those considering multiple modes more likely to prefer using the bike or public transport. Then, one sees a range of secondary factors that have an impact on some transport modes and a more marginal one on others. These factors are distance, population density, and the mobility category. Less significant but still with some explanatory value for some mode choices, there are the commuting frequency and age. Finally, the distances to the rail and local station do not provide relevant explanatory results.

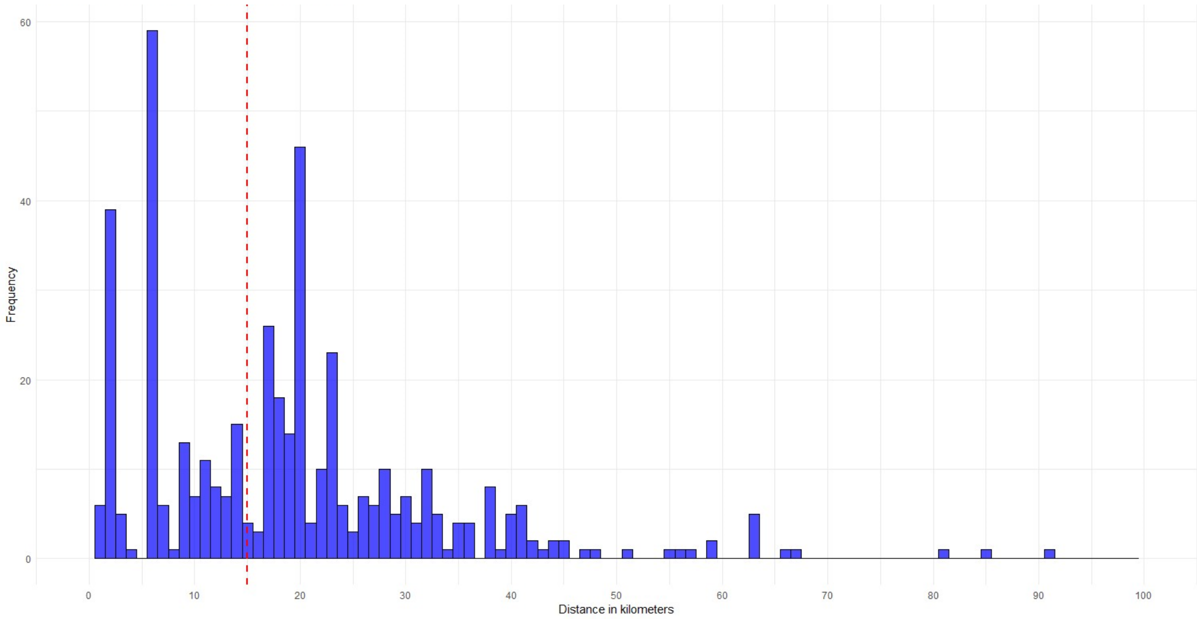
5.2 Substitution potential results

5.2.1 Potential number of affected employees

The potential number of affected employees was defined as employees for whom the car or motorcycle was the favorite mode of transportation when the distance between the home city and office address is fifteen kilometers or less. Figure 7 provides an overview of the distance distribution of car commuters at the NPO. It shows that a balanced number of employees travel below and above the fifteen-kilometer threshold. Out of the 534 employees that use the car (or motorcycle) as the most frequent mode of transportation, 182 employees lived less than 15 kilometers away from their workplace, which is the substitution potential in terms of employee count. These results show that while electric bikes are not a realistic solution for most employees commuting, a substantial share of employees do travel short distances that can be replaced by an e-bike (or other electric micromobility vehicles). For over 180 employees, providing a new incentive system in place would be relevant. If the NPO was able to effectively change the commuting habits of these employees, biking would effectively become the most prevalent mode of transport.

However, this indicator does not provide an indication of how often these employees commute, which has a large effect on the externalities created. Hence, the relevance of the “potential number of trips”.

Figure 7:Distance distribution of the NPO car commuters

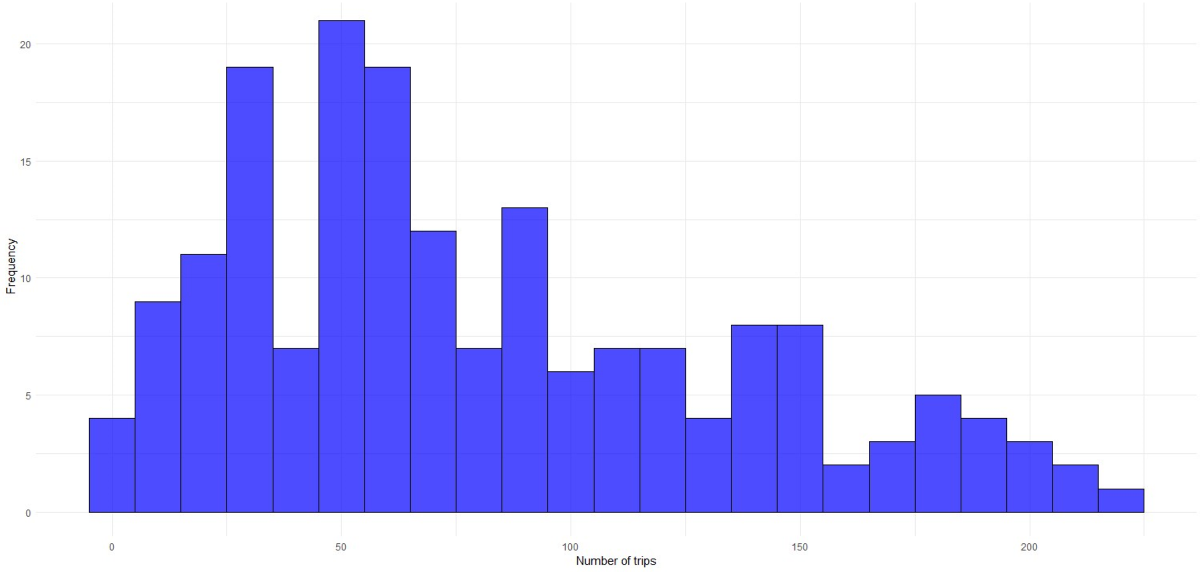


5.2.2 Potential number of trips

The potential number of trips estimates how many trips could be replaced by an alternative mode of transport such as the e-bike for distances lower than fifteen kilometers. This indicator provides a more precise understanding of the effect of employees on the natural and built environment. Figure 8 provides an overview of the number of trips conducted by each user who prefers the car throughout the monitored time period. One can observe large discrepancies with some individuals commuting over two hundred times and others traveling only a couple of times, so looking specifically at how the 182 employees commute is highly relevant to comprehending the externalities derived from their traveling habits.

Over the period of six months, the NPO employees recorded 48’109 total trips by car or motorcycle. In the optimistic scenario, the sum of all trips within 15 kilometers that can be saved was 14’750, nearly a third of all trips by car. In the balanced scenario, it was estimated that 13’340 trips could be saved. Lastly, in the conservative scenario, it is estimated that 10’390 trips could be substituted from the car, or just over 20% of all trips. These results show that electric bikes could replace between 20-31% of all trips by car, which is a transformational amount. It shows that not only a high number of commuters could change their commuting habits but also that these commuters regularly commute to work. Therefore, improving the availability of e-bikes would have a tangible impact on how commuting takes place at the NPO.

Figure 8: Distribution in the number of trips by commuters



5.2.3 Potential number of kilometers

The potential number of kilometers estimates how many kilometers could be replaced by an alternative mode of transport such as e-bikes for distances lower than fifteen kilometers. While the potential number of trips provides a clearer vision of how many times a private car could avoid taking the road (and thereby avoiding externalities such as additional traffic, noise pollution, etc.), it does not distinguish between shorter and longer trips. As one can see in Figure 7, there is a significant variation in distance within the fifteen-kilometer threshold. This indicator remediates this by summing the product of the distance (between the city of residence and the registered office) and the number of trips recorded by each commuter. Hence, the potential number of kilometers saved provides a clearer picture of the impact of each commuting trip and is a stepping stone to quantify the operational emissions of vehicles.

During the observed time period, the NPO employees recorded 1’334’951 kilometers of driving by car (or motorcycle).

Within the optimistic scenario, whereby all trips of up to fifteen kilometers can be substituted from the car, it was estimated that about 100’500 kilometers could be substituted, so about 7.5% of all kilometers traveled by car (excluding business travel). In the balanced scenario, it was estimated that 86’889 kilometers could be substituted. Finally, the conservative scenario estimates that about 66’789 kilometers could be saved, or about 5% of all kilometers driven during the time period. These estimations show that substitution potential in distance is between 5-7.5%, which is low but understandable given that we only look at commuters traveling short distances to the office. The results show that while a high number of employees and number of trips could be substituted for e-bikes, the number of kilometers that would be saved by the NPO employees is more marginal.

5.2.4 Synthesis

This investigation into e-bike potential within distances of fifteen kilometers suggests that nearly 40% of car commuters (whereby the car is the most frequently used travel mode) at the NPO could switch to an e-bike for at least some of their trips. Considering these short-distance commuters, I estimate that between 20-31% of all employee, trips could be avoided (10’390-14’750 trips) within the time period. However, while the substitution potential for employees and the number of trips is high, the substitution potential is by default limited to shorter trips. As a result, the total number of kilometers is more marginal with a potential of 5-7.5% of the total number of kilometers being substituted.

6. Discussion & Conclusion

Commuting behavior decisions are complex and depend on many factors, sometimes difficult to quantify and subject to a high level of heteroskedasticity. Some of these explanatory factors are functional such as time, cost, accessibility, the built (incl. work) environment, and other socio-demographic factors. Other non-functional factors are less tangible but can be as important to some individuals and include and not limited to convenience, comfort, habits, social and personal norms, as well as attitudes and personality traits. However, mapping complex behaviors is possible, only if data quality and sample sizes are sufficient.

For daily traveling habits, the data collection process has remained mostly archaic with previous studies relying on costly one-time or periodical surveys enquiring about past traveling habits. They are expensive to conduct, tedious for the individual to fill in, and only information about stated preferences is provided, and doubts persist on how representative a sample is. As a result, no published study (as of September 2023) has been able to incorporate a comprehensive range of factors, to gain insights on their relative significance and interactions, as would be beneficial to provide a more complete picture.

This study is a first step to tackling these two challenges. Instead of relying on one or multiple surveys, data was directly collected from a mobility as a service provider during a period, during which all employees of a company input via an app travelling details for reimbursement purposes. This process provides a much more systematic understanding of daily commuting habits over a longer period. Of course, there is a risk of dishonesty on the app as commuters may be tempted to increase reimbursements, but random checks are in place (with significant disciplinary action), so one can assume that there are no systematic errors, and data quality is sufficiently high.

The results suggested that the number of modes considered when traveling to work was the key factor in determining if the car was the primary modal choice. There is a high level of association between being a unimodal commuter and the probability of being car-dependent, providing further evidence of a lock-in mechanism for road transport (Klitkou, et al., 2015). Conversely, using two or more mode choices throughout the time period is associated with an increase in the probability of preferring alternative mode choices such as public transport or the bike. The effects may warn against investment in expensive Park & Ride infrastructure and may not have the desired effect if car commuters are unimodal and unwilling to change to a different mode. Other significant factors were the distance, population density, and mobility category. As distance increases, the probability of the bike being the most frequent mode choice of transport decreases and conversely with the car and intercity trains. With regards to population density, the results confirm results from previous literature on the topic, whereby a higher population density in the place of residence decreases the likelihood of using the car most frequently in favor of other mode choices. The effects of the mobility category show that the NPO's current mobility policy clearly encourages the use of cars at the expense of local transit. It's an interesting example of how a policy that does not encourage a mode choice by design may have unintended consequences on the individual mobility behavior[3]. Finally, commuting frequency and the year of birth were relatively weaker determinants. A higher commuting frequency increased the probability for local transit to be the preferred mode choice and conversely for NS train travel. These results are not in line with the previous literature on the subject that would associate a higher commuting frequency with a higher probability of being a car user (Ton et al., 2020). Regarding the year of birth, younger employees tend to prefer using the car whereas older employees prefer using the bike. These results confirm the findings of Ton et al. (2020) and are inconsistent with the findings of Calastri, Hess, & Choudhury (2019) who conducted research in Italy. This suggests that generational perception of modal choice may be highly country-specific.

While this data retrieving method provides a large dataset based on high data quality, one significant drawback relative to a survey is that the factors available to analyze are mostly predetermined, instead of having the possibility to choose them based on previous research in a survey. Therefore, while this research does provide insights into a population (instead of a sample) for eight factors, one of the main limitations of this research remains that it still fails to provide a complete picture needed to fully grasp the challenge needed to find optimal and practical solutions.

One of the key particularities of this research is that is based on an entire population instead of a population sample. This is very advantageous as the results are not subject to sample-based biases. However, the explanatory scope of this research is more limited. Of course, it provides insights into what the determinant factors of the population are i.e., the NPO. But can any of the results of this population be generalized to a wider group such as the wider population living in the Netherlands or other countries? In other words, to what extent does the current sample size represent the wider population? The findings from the descriptive statistics may be helpful in this regard.

The NPO employees are located, on average, fifteen kilometers away from work and about 55% of them use the car as the most frequent travel mode. The dataset only provides limited socio-demographic information on the employees, which would provide evidence on whether the employees are representative of the overall population. Further, it must also be accounted for that the NPO is not a classic private company, therefore, it is prone to attract groups sharing similar characteristics and values. What is known is that employees of the NPO predominantly live in urban areas in the region of North Holland and are forty-four years old on average. This is slightly older than the average age population of the Netherlands (42.4) and North Holland (42.6) (CBS, 2023); (AdminStat, 2023). Based on the

[3] One must also consider that those who are affected by this policy travel most frequently for business-related trips. It is impossible to verify if the fact that this group uses more the car is mostly due to the characteristic of the trip destinations or the policy itself.

information available, there is little evidence suggesting that the employees are a representative sample of the Netherlands or North Holland.

As e-bikes are increasingly being considered a substitute for cars for short distances (especially in the Netherlands where cycling infrastructure is highly developed), the last part of this research quantified the substitution potential of cars for e-bikes for distances of less than fifteen kilometers. The investigation focused on three tangible parameters, the number of affected commuters, the number of trips, and the number of kilometers. The results were a mixed potential with a high potential of car commuters (nearly 40%) being able to substitute some of their car trips. However, if this commuter group would have an e-bike available, there is no guarantee that it would replace all car trips, due to factors such as distance, weather, or other personal motives. Therefore, three scenarios based on the distance were derived to calculate the substitution potential in trips and kilometers. The results suggested that while a significant portion of trips could be substituted (20-31%), this would only represent between 5-7.5% of all kilometers driven by the NPO employees for commuting purposes.

The results are ambiguous but would likely be found in a large number of companies with a significant number of people using the car while commuting small distances. Yet, those distances are only a fraction of the total distance driven because most kilometers are driven by commuters living large distances from the office.

In a business environment where Dutch companies[4] must start reporting CO2 mobility emissions, as well as more broadly reporting and reducing externalities generated at all scopes of the value chain (as defined by the Greenhouse Gas Protocol), some companies are also looking for practical solutions to lure employees away from their cars (Netherlands Entreprise Agency, 2023); (Greenhouse Gas Protocol, 2023).

However, the results concerning the number of kilometers substituted suggest that the rate of carbon emissions saved with a shift to e-bikes to be fractional, given that emissions are generally proportional to the number of kilometers driven. As a policy implication for the company to reduce commuter-related CO_2 emissions, I would suggest not supporting the shift to e-bikes since CO_2 emissions from short-distance commuters are marginal. Instead, I suggest a policy targeting employees living longer distances from the office, and perhaps, encourage a switch to an electric car, public transportation, home-working, or even a change of home or office location.

Another interesting result for the NPO regards how the mobility budget is positively (negatively) associated with an increase in the probability of conducting most trips by car (local transit) relative to other mode choices. The beneficiaries of the mobility budget are employees who must frequently travel to apartments on short notice, hence, they require a high level of flexibility. The car has historically

[4] businesses with 100 employees or more

been associated with the highest level of flexibility—being able to drive anytime, anywhere. Inversely, this flexibility also enhances the lock-in mechanism. For example, an employee aware that there is a positive likelihood of having to visit an apartment on a given day that may be inaccessible by other modes will be drawn to commuting by car to work even if other mode choices would be more adequate. Hence, this lock-in effect of the car leads to additional CO_2 emissions from the derived commuting choice.

Another policy recommendation for the NPO is to update the mobility budget policy that currently leads to sub-optimal use of the car by employees while fulfilling their need for a high level of flexibility. This can be done by partnering with diverse mobility providers (of bicycles, mopeds, and electric cars) that are well-implemented in the operating region of the NPO. Such partnerships would provide employees with the most adapted travel mode for whatever the destination is. After open discussions with concerned employees and adequate partnerships, part of the mobility budget should be removed in favor of subscriptions to shared mobility providers.

Finally, the current discourse on externalities focuses on CO_2 emissions. Yet, it has been long-established that other externalities such as diverse air pollutants concentration (Heath Effects Institute, 2010), traffic congestion (Santos, et al., 2010), or noise and heat pollution (Bell & Galatioto, 2013); (Petralli, et al., 2013). In other words, simply switching to an electric car or less mileage with a combustion engine does not solve these other urban challenges associated with car-centric mobility.

Currently, the tangible benefit for companies to encourage active transportation modes in urban areas for small distances rests on keeping a healthy workforce. However, further research is still needed to assess the business case for increasing the accessibility of e-bikes for employee health.

As the results of the second analysis have shown, the substitution potential regarding the number of trips is much more significant with up to a nearly third of all trips being able to be avoided. In this sense, increasing the availability of e-bikes has the potential to significantly contribute to the reduction of these externalities, without mentioning the health benefits of active mobility. However, current regulation does not distinguish the type of environment where emissions are generated, so the private sector is currently not incentivized to reduce the number of trips done but only the emissions associated with the distance. Hence, the first step must come from local authorities who aspire to become less car-centric. Financial capability to encourage the substitution of large private vehicles in favor of smaller and energy-efficient vehicles such as e-bikes can be built by increasing the revenue from parking fees to subsidize the availability of light electric vehicles, as well as charging stations.

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