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Determinants of car-sharing use: Autonapůl Case study

Bachelor's thesis

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Prague, July 13, 2023

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Abstract

This thesis investigates car-sharing use by subscribers of that time of Autonapůl, the longest operated App platform in the Czech Republic. First, we analyse the mileage of the App subscribers and survey respondents, finding different behaviour patter among the users who did not participate in the survey. Survey participants use the App more actively (89% with non-zero km) and drive on average more (154 km a month) than the App users who did not agree to participate in the survey (65% and 85 km, respectively). Then, we analyse demand on kilometres driven by survey respondents, treating the potential selectivity due to reported zero mileage. We compare OLS and two selectivity models - two-stage Heckman and two-part models. The study also examines the impact of usage frequency on kilometres driven. Those who drive more frequently also drive more - users who used the App at least once a week drive almost ten times more kilometres than those who used the App less than once a month (395 km versus 53 km a month). We find that age, use for leisure purposes, satisfaction, and having children are associated positively, and car ownership is associated negatively with mileage driven by car-sharing. This study enhances the topic of car-sharing by examining determinants of car-sharing use and its underlying factors using statistical methods.

Keywords Car-sharing, User behaviour, Sample selection problem, Heckman two-step estimator

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Abstrakt

Tato práce zkoumá využívání sdílení automobilů tehdejšími účastníky Autonapůl, nejdéle provozované platformy v České republice. Nejprve analyzujeme kilometrový nájezd předplatitelů aplikace a respondentů průzkumu, přičemž zjištujeme odlišný vzor chování u uživatelů, kteří se průzkumu nezúčastnili. Účastníci průzkumu používají aplikaci aktivněji (89% s nenulovým počtem ujetých km) a najezdí v průměru více (154 km měsíčně) než uživatelé aplikace, kteří nesouhlasili s účastí v průzkumu (65%, 85 km). Poté analyzujeme poptávku po kilometrech ujetých respondenty průzkumu, přičemž ošetříme možnou selektivitu způsobenou vykazovaným nulovým počtem ujetých kilometrů. Porovnáváme OLS a dva modely selektivity - Heckman two-step a Two-part model. Studie rovněž zkoumá vliv frekvence používání na ujeté kilometry. Ti, kteří jezdí častěji, také více ujedou - uživatelů, kteří aplikaci používali alespoň jednou týdně, ujedou téměř desetkrát více kilometrů než ti, kteří aplikaci používali méně než jednou měsíčně (395 km oproti 53 km měsíčně). Zjistili jsme, že věk, používání pro volný čas, spokojenost a to, uživatel má děti, souvisí pozitivně a vlastnictví automobilu souvisí negativně s kilometry ujetými prostřednictvím aplikace. Tato studie rozšiřuje téma sdílení automobilů tím, že pomocí statistických metod zkoumá determinanty využívání sdílení automobilů a jeho základní faktory.

Klíčová slova	Car-sharing, Chování uživatelů, Problém výběru vzorku, Heckman two-step estimátor
Název práce	Determinanty využití car-sharingu: případová studie Autonapůl

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Chapter 1

Introduction

Car-sharing has developed as an alternative to traditional automobile ownership, with advantages such as decreased traffic congestion, improvement of parking issues, lower carbon emissions, and offering of a cost-effective mobility option. This unique transportation concept allows users to rent automobiles short-term, contributing to resource efficiency and encouraging a shared economy (Ferrero *et al.* 2018). As car-sharing grows in popularity worldwide, several studies have been conducted to understand better its influence on other travel modes of transportation, e.g. Ceccato & Diana (2021); Becker *et al.* (2018) and member behaviour, such as incentives to join (Becker *et al.* 2017a) and determinants of use (Giesel & Nobis 2016; Becker *et al.* 2017c). The findings in such papers offer valuable insights for policymakers for infrastructure development, policy formulation, and the implementation of effective incentivising strategies. Additionally, they provide practical information for car-sharing companies, helping them develop marketing and pricing strategies as well as organisational structure, to improve the quality and competitiveness of their service.

This thesis examines the factors that influence the utilisation of the Autonapůl car-sharing service measured by kilometres driven by a shared car during a month. The study will employ Ordinary Least Squares (OLS) regression and address the sample selection problem using the Two-step model and the Hackman two-step estimator (Smutna & Scasny 2017; Belotti 2015; Heckman 1976). This research will be the first to analyse the dataset provided by the Environmental Centre of Charles University in collaboration with Autonapůl, the longest-standing car-sharing service in the Czech Republic, using this methodology.

The thesis is structured as follows: Chapter 2 presents a literature review on car-sharing, Chapter 3 provides information about the data set and data preparation. Chapter 4 describes the methods used. Chapter 5 presents the results and discussion and Chapter 6 concludes the thesis.

Chapter 2

Literature review

2.1 Definition of car-sharing

Shared vehicle mobility reduces traffic congestion and provides more affordable and sustainable transportation options. Car-sharing is one form of shared mobility service which allows individuals to rent out vehicles for short periods. Another form of shared mobility is car-pooling, where people coordinate and travel in one car, usually regularly and based on the convenience of their similar destinations.

Car-sharing services have different forms. The first distinction is based on the provider: the Business-to-consumer (B2C) or the Peer-to-peer (P2P) rental system. The former utilises a fleet owned by a company that provides vehicles to individuals. The latter operates as a platform where individuals can easily rent their cars to others.

Car-sharing operates on an online platform where individuals agree on use conditions, including payment details, insurance and liability agreements. Different pricing mechanisms usually include a signing fee, a subscription plan and pay-per-use, calculated by the time of use or the distance driven.

There are two main models of car-sharing. Firstly, station-based car-sharing, which has designated stations where customers can rent and return vehicles. Round-trip car-sharing is a more restricted form of this model, where pick-up and return locations must be the same. Secondly, free-floating car-sharing offers the option to access and return the vehicle to any parking spot within a designated area.

2.2 Car-sharing in Czech Republic

Autonapůl is the first car-sharing program in Czechia, operating since 2003. It is currently available in 13 Czech cities. Autonapůl offers a wide variety of vehicles ranging from smaller electric to larger vans for eight people. It is a free-floating service as it has distinct vehicle parking zones. However, they cover just parts of the cities.

Anytime is an Italian service operating in the Czech Republic since 2019. Their fleet consists of over 700 Toyota hybrids, operating only in Prague. A considerable advantage of this service is that it has pick-up and drop-off locations almost all over Prague, and they have permission from the city to park vehicles in "blue" zones.

According to Anytime's research from 2022, 17% of Prague citizens use car-sharing, which is a 6% increase since 2021 (Feedit 2022).

Car4way is another free-floating service that has been operating since 2014. It offers over 700 vehicles in its fleet in Prague and Brno, similar to Anytime they provide free parking in special zones within the city centre. Their offer vehicles in four categories based on their size and fuel type, one being electric cars.

GreenGo was a car-sharing service in Prague with a purely electric vehicle fleet which expanded from Budapest. However, they operated for just two years, between 2020 and 2022, until they left the market.

The final service is AJO car-sharing which is less popular than previously mentioned. However, their service is most affordable for longer trips. They offer Skoda Fabia cars in Prague in Brno. Their service is free-floating, but the available zones only cover parts of the cities.

2.3 Factors and effects of car-sharing on scale and structure of mileage

Car-sharing systems have been previously thoroughly studied to determine their effects on modes of transport and the factors influencing individuals' decisions to join and use their services. Studies on this subject use either stated preferences, revealed preferences data, or both. Compared to revealed preferences, the stated preferences data have an advantage in anticipating the future decisions of respondents by presenting hypothetical scenarios that do not currently exist. This approach allows researchers to explore outcomes of potential situations and predict individuals' behaviour (Kroes & Sheldon 1988). The revealed preference data are actually observed; therefore, the results are more accurate and not influenced by biases (Wardman 1988). To avoid the limitations of each valuation technique, a possible solution may be to combine both stated and revealed preferences. However, only a few authors, e.g. Becker *et al.* (2018), used this approach.

Existing research on this topic also differs in the type of sample. The targeted population can be solely car-sharing users to understand their common characteristics (Giesel & Nobis 2016). A sample representing the whole population is ideal for estimating the modal split. However, car-sharing is a relatively new advancement; thus, the number of respondents actively participating in the service may now be sufficient. As a result, only a few studies use a sample representing the whole population, typically overcoming these limitations using a larger sample than usual (Becker *et al.* 2017c;a; Ceccato & Diana 2021).

2.3.1 Factors on car-sharing membership subscription

In order to use a car-sharing vehicle, people need to join a car-sharing organisation. Sign-up usually involves paying a deposit, subscribing to monthly fee payments, or both. Kim *et al.* (2017) found that reducing these costs is more efficient in inducing car-sharing membership than reducing per-kilometre or per-minute costs.

The first factors influencing an individual's decision to purchase a car-sharing subscription are fixed and variable costs connected to using a private vehicle. Variable costs include parking fees, tunnel or highway fees and fuel prices (Becker *et al.* 2017a). Fixed costs of owning a personal car, including purchasing price, insurance and maintenance, can make car-sharing a more affordable substitution as these costs are split between multiple users (Martin & Shaheen 2016; Steininger *et al.* 1996).

Another factor is the risk of possible unavailability of shared vehicles. Vehicles can either be available further away or not at all. Kim *et al.* (2017) studied how this uncertainty can negatively affect joining a car-sharing service as individuals try to maximise their utility.

However, good public transport accessibility can partly offset this effect, allowing individuals to get closer to the shared vehicle (Becker *et al.* 2017a;

Martin & Shaheen 2016). Well-functioning public transportation or even bike-sharing can thus induce car-sharing membership (Kim *et al.* 2017).

Finally, the positive perception of car-sharing can motivate people to join. An individual's attitude and perception of their surroundings can encourage people to make more environmentally beneficial decisions, and this can mean choosing to subscribe to car-sharing (Kim *et al.* 2017; Liao *et al.* 2020).

The effects of these factors vary across different socio-demographic groups. People with higher education level tend to consider the environmental impact and infrastructure benefits of their travel behaviour more. On the other hand, people from lower-income families are more likely to get influenced by variable costs (Becker *et al.* 2017a).

2.3.2 Factors on the frequency of car-sharing usage

When car-sharing becomes a viable option, several factors can impact when and how often individuals use it. Becker *et al.* (2017c;a) observed that the station's location does not significantly affect the frequency of use. Furthermore, Liao *et al.* (2020) argued that changing any system attributed does not have an effect.

An individual's availability of other forms of transportation creates more options to choose from comfortably. Becker *et al.* (2017c) have discovered that owning a public transport card reduces the use of car-sharing, similar to owning a private vehicle.

The cost of transportation affects daily decisions about transportation. Lower per-mile or per-hour fee induces the use of car-sharing. In addition, the possibility of free parking, especially in the city centre, increases car-sharing demand.

Finally, the purpose of travel plays an essential role in decision-making. People are more likely to use car-sharing when carrying heavy objects, which can be either for leisure purposes or shopping. Furthermore, people use one-way car-sharing for travelling to an airport or other places where it is inconvenient to park a personal car (Becker *et al.* 2017c).

2.3.3 Effect on car ownership

The first critical impact of car-sharing is its potential to reduce car ownership, as individuals may opt to use shared vehicles rather than own them. It is an essential effect because reducing the number of cars creates less manufacturing emissions and decreases demand for parking spots, which is an interest to policymakers.

Numerous studies have documented this effect using different methods, finding that car-sharing members are likelier to give up their vehicles or delay purchasing a car than non-members. Although all the mentioned studies confirm this effect, the number of private cars reduced by a single car-sharing vehicle varies between 2.5-13 (Vine & Polak 2019).

The first technique used is collecting revealed preference data (Vine & Polak 2019; Becker *et al.* 2017c; Giesel & Nobis 2016), asking current users whether they got rid of a vehicle or have forgone a purchase after joining the service. Becker *et al.* (2018) combined both stated and revealed information about car-sharing users to arrive at more accurate results.

Moreover, the papers investigated whether the impact of car-sharing on car ownership differs between free-floating and station-based models, with the former demonstrating a more significant substitution effect. This potential for car-sharing to reduce car ownership is a promising development in promoting sustainable transportation practices. However, mentioned revealed preference data was collected mainly on ”early adopters” of the car-sharing transportation system, who may behave differently than a representative sample.

Another technique is analysing stated preference data, e.g. Liao *et al.* (2020); Vine *et al.* (2014), which allows sampling of the whole population on hypothetical car-sharing scenarios. Giesel & Nobis (2016) found that most car-sharing users do not plan on shedding a car. They further asked them to specify the conditions under which they would consider it, finding that the choice could be affected by car-sharing infrastructure, higher costs for using private cars or better-interconnection of other transport modes.

Later studies are even more critical and suggest that the previous papers overestimated the effect (Bucsky & Juhasz 2022). Kolleck (2021) further demonstrates the change in motorisation rates before and after introducing a car-sharing scheme using empirical data about car-sharing usage and registration of data on new vehicles. Nijland & van Meerkerk (2017) discovered that rather than completely replacing private vehicle ownership, in most cases, car-sharing works as a substitute for owning a second or third vehicle. Giesel & Nobis (2016) also mention that car-sharing may encourage individuals to own cars by allowing customers to become accustomed to private vehicle use without any obligations or longer-term commitments.

Some studies focus on private car trip replacement due to car-sharing instead (Firnkorn & Muller 2011). Vine & Polak (2019) observed that people who replace more trips have a higher chance of shedding or not buying a car. Liao *et al.* (2020) focused on this relationship, concluding that 40% of respondents would replace some trips after introducing a car-sharing service. However, only 20% would consider replacing their vehicle. They found these two effects to be unrelated, thus suggesting that they should be studied separately.

2.3.4 Effect on public transport

Car-sharing affects public transport in multiple ways. Ceccato & Diana (2021); Clewlow (2016) argue that it is both a complement and a substitute, as it either reduces or increases the use of public transport for different people.

Car-sharing may complement public transport, particularly for first-mile and last-mile connectivity, making shifting from private automobiles easier (Martin & Shaheen 2016). It also satisfies transportation demand when public transport is not easily accessible, e.g. at night Wagner *et al.* (2016); Becker *et al.* (2017c) or when it is more suitable for occasionally longer or discretionary trips (Becker *et al.* 2017b). For car-sharing users, in case a vehicle is unavailable, Nijland & van Meerkerk (2017) observed that they are most likely to opt for a substitute in the form of public transport. However, Becker *et al.* (2017c) found this to be true just with free-floating car-sharing, with station-case car-sharing users postponing the trip until the vehicle becomes accessible again.

On the other hand, car-sharing can decrease public transport use when used for daily commute trips instead (Cervero *et al.* 2007; Ceccato & Diana 2021). Free-floating car-sharing substitutes public transport in such occasions due to its flexibility (Becker *et al.* 2017b; Vine *et al.* 2014). When studying the characteristics between members and non-members, Becker *et al.* (2017c); Clewlow (2016) found that most car-sharing customers have already been used to commuting with public transport.

The car-sharing effect on public transport varies based on the service model implemented (Becker *et al.* 2017c; Vine *et al.* 2014). According to (Becker *et al.* 2018; Ceccato & Diana 2021), people use station-based car sharing sparingly. Therefore, it generally complements public transport used for everyday commutes. However, after introducing the service, Martin & Shaheen (2016) observed on data on car-sharing users in the USA most free-floating car-sharing customers use less public transportation than before. These findings are not directly comparable to Europe scenarios as the quality of public transit is different. However, Becker *et al.* (2017c); Vine *et al.* (2014) confirm the effect of reduced public transport usage on stated preference choice data from European cities.

2.3.5 Effect on kilometres driven

Previously mentioned papers suggested that car-sharing can reduce car ownership and use. Furthermore, it can induce a shift towards combined transport, including more environmentally friendly options such as public transport, bikes, and walking. However, the higher per-kilometer affordability of car-sharing compared to car ownership can create various rebound effects. One affects the total kilometres driven when lower prices lead to increased consumption of car-driven kilometres, thus offsetting the intended environmental benefits (Sorrell & Dimitropoulos 2008). Nijland & van Meerkerk (2017) examined the increase in demand for kilometres driven caused by the sole existence of car-sharing. The researchers asked car-sharing customers how they would make their recent trips if car-sharing were not an option, resulting in 15% of participants not completing the trips.

The switch in transport modes may also induce changes in car-driven kilometres. On the one hand, the decrease in car usage is affected by the effect of car shedding. Users have to increase their creativity whilst travelling, newly combining their travels with public transport, bikes, and walking. On the other hand, the increase in kilometres is most prominent with customers switching from public transport use to cost-efficient, user-friendly, and easily accessible transportation service of car-sharing (Jung & Koo 2018; Nijland & van Meerkerk 2017).

The evidence from North America suggests that car-sharing significantly decreases overall kilometres driven (Martin & Shaheen 2016). Less developed public transportation than in Europe and more common personal car use and reliance can be used to interpret these observations. As a result, from previously mentioned effects, a type of switch which decreases kilometres driven is more frequent. Cervero *et al.* (2007) compared revealed information on travel habits over 20 days of car-sharing users with a non-user control group and observed that people, on average, reduced their daily vehicle miles travelled faster in a time of rising fuel prices. This effect is explainable, with car-sharing use being affected significantly by variable costs.

Martin & Shaheen (2011) used data on the travel habits of car-sharing customers a year before and after they joined the service. Although some households increase their mileage due to gained access to cars, others reduce it by switching from private vehicles to car-sharing, resulting in a net decrease in vehicle miles travelled.

Martin & Shaheen (2016) confirm this trend with data on car-sharing customers from five large USA cities, including vehicle miles travelled which were prevented by forgoing private vehicle purchases (estimating from the information collected how much more frequently are private cars used compared to shared ones by one individual). In addition, they observed this decrease even after including miles driven by car-sharing employees during car redistribution.

Studies from European cities also suggest a net decrease in vehicle kilometres travelled. Firnkorn & Muller (2011); Vine *et al.* (2014) confirmed this effect by the stated preference approach about hypothetical scenarios, and Giesel & Nobis (2016); Nijland & van Meerkerk (2017) used revealed preference data on car-sharing customers to reach the same conclusion. Vine *et al.* (2014) further differentiated the stated preference scenarios between introducing station-based and free-floating car-sharing and different possible implementation areas (inner and outer parts of the city). Previously discussed effects on public transportation and private car ownership align with the findings. Station-based car-sharing introduced all over the city has the highest reduction of kilometres driven. Free-floating car-sharing in the inner parts leads to the lowest total reduction in kilometres. Nijland & van Meerkerk (2017) observed the same trends in car-sharing customers.

A more elaborate technique of studying the change in vehicle kilometres travelled using revealed preferences is in the form of travel diaries, collected either by recalling or recording travel behaviour by respondents or via GPS data. Although this approach is the most accurate, data collection difficulties lead to small or unrepresentative samples; therefore, only a few researchers have used it, e.g. Cervero *et al.* (2007). Becker *et al.* (2018) used the travel diary method. However, due to an insufficient sample of car-sharing users, their research allowed only for qualitative analysis. The authors suggest that car-sharing triggers a modal shift from private car ownership to public transportation. Thus, it may lead to a reduction in kilometres travelled by car.

2.3.6 Effect on the environment

Some papers on car-sharing focus their research on the environmental implications of car-sharing. The effect is complex as it includes both upstream and downstream impacts. Due to car-sharing, vehicles are better utilised to their full potential. There is a reduction in manufacturing and fuel production, lowered demand for parking, improvement of other modes of transport and decreased vehicle scrappage all add to this effect (Amatuni *et al.* 2020). These effects are often evaluated by calculating the change in CO2 emissions caused by car-sharing. Similarly to the effects mentioned above, a switch from private cars causes a decrease whilst the one from public transport causes an increase. Nijland & van Meerkerk (2017) states that these two effects together add up to a net reduction. In addition, CO2 emissions are decreased due to fewer vehicles in rotation (Nijland & van Meerkerk 2017; Martin & Shaheen 2016).

Car-sharing fleets usually consist of newer and smaller vehicles which are more fuel efficient. In some cases, the service utilises electric or hybrid cars. Due to this fact, even when customers replace their private vehicle for car-sharing without the mileage reduction, the change is environmentally beneficial (Liao *et al.* 2020).

As a negative side effect, saving on transportation costs can lead people to spend their money elsewhere, possibly on goods that generate some emissions (Vélez 2023).

Lastly, car-sharing is a step towards increased societal equity. People who would not have access to driving a car due to the high fixed costs of owning a private vehicle can use car-sharing when in need of driving a car themselves, e.g. carrying heavy objects, trips to the hospital and work-related occasions.

2.4 Segmentation

Car-sharing users can be divided into groups according to different criteria like socio-demographics, attitudes and travel pattern behaviour. Knowing this segmentation is helpful for car-sharing providers to develop better advertising to target their potential customers and to tailor the service to current users.

2.4.1 Socio-demographics

The first way of segmentation is based on socio-demographic variables, which refer to gender, age, level of education, income and occupation, and household size.

Males are likelier to join car-sharing services (Becker *et al.* 2017c;a; Ceccato & Diana 2021). Giesel & Nobis (2016) found this difference between genders as high as 74% and 80% of male users at two car-sharing services. On the contrary, Martin & Shaheen (2011) are a rare exception, with their research stating that 55% of their studied sample of car-sharing members were women.

Car-sharing members are typically younger than the average population (Becker *et al.* 2017c;a). Giesel & Nobis (2016) found the average age at 36 and 45 studying two different services and that younger than the average population members use the service more frequently. Ceccato & Diana (2021) support this, with their sample having the average and mode in the age group 35-44 years old.

Another crucial factor is education. Car-sharing members tend to be more educated than the average population (Giesel & Nobis 2016; Becker *et al.* 2017a). Data from Ceccato & Diana (2021) show that half of the car-sharing users from their sample have a Master's degree or higher. Becker *et al.* (2017c) argue that education has a much higher impact on car-sharing membership than on frequency of use.

Income also affects car-sharing membership, with higher-earning individuals being more likely to join and use the service more frequently (Ceccato & Diana 2021; Becker *et al.* 2017c). Becker *et al.* (2017a) suggest that this might be due to higher-education professions requiring more flexibility in mobility. While Giesel & Nobis (2016) state that 80% of the members studied were full-time employed, Becker *et al.* (2017c) report that students and freelance workers are likelier to join the service than other groups.

The research conducted by Ceccato & Diana (2021) and Becker *et al.* (2017a) suggest that the size of a family and having children negatively affect car-sharing membership and the frequency of use. Giesel & Nobis (2016) state that most frequent members are from one or two-person households. Probable explanations are that car-sharing vehicles do not contain car seats for children of larger families or that they can utilise their cars more effectively with higher car transportation needs.

In summary, a typical customer has been a usual "early adopter" of technology and innovation. However, this might be just the first wave of data documented, and future user demographic might be different (Ceccato & Diana 2021).

2.4.2 Attitudes

Another element that influences transport mode choice is an attitude toward car-sharing. Perception of the economic, environmental, and social benefits of using the service plays a significant role in decision-making about car-sharing usage (Liao *et al.* 2020; Mattia *et al.* 2019).

Society perceives car-sharing as efficient, useful and as a ”greener” alternative to private cars (Ceccato & Diana 2021). Especially people with higher education and income can choose environmentally conscious behaviour as they have multiple affordable options. Thus, the personal stance towards ecological responsibility is an essential factor (Liao *et al.* 2020). According to Becker *et al.* (2017a), attitudes should be included in modelling concerning car-sharing.

2.4.3 Trip patterns

Car-sharing users can be divided based on their trip patterns. On the one hand, some of them use the service for everyday necessary commutes like travelling to work or grocery shopping. On the other hand, some use the service less frequently as they rent the car just for leisure trips once in a while. For these two main groups, travel time and distance differs significantly (Cervero *et al.* 2007). Whilst the first type of user highly prefers free-floating car sharing with the additional flexibility, the latter does not mind the station-based system (Liao *et al.* 2020).

2.5 Methods

Above mentioned research papers on car-sharing use a range of different econometric methods. These modelling techniques are used to forecast the demand for car-sharing services, calculate the impact of different factors on car-sharing usage and analyse how car-sharing affects the environment and other modes of transportation.

2.5.1 Analysing car-sharing subscription

Ceccato & Diana (2021); Becker *et al.* (2017c) use binary logit models to model determinants of car-sharing subscription decisions. Becker *et al.* (2017c) used probit models to depict the dependent variable car-sharing membership with socio-demographic characteristics as independent variables. Furthermore, they used the ordinal probit model to describe the frequency of use of car-sharing services by the members.

2.5.2 Analysing milleage

Both Jung & Koo (2018) and Cervero *et al.* (2007) use linear regression to predict how adopting car-sharing services affects the user's average mileage travelled. They concluded different results, Cervero *et al.* (2007) stating that car-sharing reduces mobility and Jung & Koo (2018) suggesting that car-sharing increases mobility and connecting this effect with an environmentally friendly perception of car-sharing. When individuals perceive car-sharing as a greener transportation alternative, they allow themselves to travel more. Furthermore, Jung & Koo (2018) also used linear regression to model public transit and private car substitution rate. Dependent variables in these cases include socio-demographic variables, attitudes towards the environment and car-sharing service attributes.

2.5.3 Analysing car ownership

Jung & Koo (2018); Vine & Polak (2019); Giesel & Nobis (2016) use binary logit models to describe the relationship between car-sharing on car ownership, specifically the likelihood of shedding or forgoing a purchase. Cervero *et al.* (2007) used the ordered logit model to describe vehicle ownership, with the differentiation between different numbers of vehicles. Becker *et al.* (2018); Cervero *et al.* (2007) used the difference-in-difference method to determine the effect of introducing a free-floating car-sharing service on car ownership. Independent variables in these papers are based on literature review and or personal assessments of the authors and include car-sharing characteristics, other modes of transportation characteristics, socio-demographic variables and attitudes.

2.5.4 Analysing modal choice

Cervero *et al.* (2007) used a multinomial logit model to model a modal split between car-sharing, public transport, private vehicle, car and bike. Becker *et al.* (2017a) used a multivariate probit model to jointly model four modal split options. This paper is specific in identifying the factors included in the model. While others depend mainly on the literature review or personal assessment, these authors used maximum likelihood and ordered logit models to determine the most relevant factors.

Chapter 3

Data

3.1 The datatset

We analyse car-sharing usage by the Autonapůl App subscribers. During the original research, there were 642 members of Autonapůl. These people define our target population. There are two sources of data. First, Autonapůl provided information about kilometres and time driven, money spent, length of the membership and city of use for all members (N=642). We call this part of subscribers "users". Then, The Charles University Environment Center contacted all active users in the summer of 2017 (N=634) with a request to participate in a survey. Since English-speaking users are a minority among users, they were not contacted.

The questionnaire was pretested with a few subscribers and the owners of Autonapůl during Spring 2017. Respondents were interviewed online, using computer-assisted web- & self-interviewing survey mode.

Answers were collected from 12 August 2017 to 15 September 2017, and users were incentivised to answer by chance to win a price in credit for future use of the car-sharing service. The data are cross-sectional, as the questionnaire collection time and measured period are the same for all subjects.

Overall, 308 people completed the survey, resulting in a 48.6% response rate and covering 48.0% of all App subscribers. We call this part of subscribers "respondents". Due to the voluntary nature of the questionnaire, the characteristics and opinions deducted from the questionnaire might only be representative of part of the sample.

The final version of the data from the questionnaire consists of a part about using the car-sharing service, preferences, and opinions and one about the socio-demographic characteristics of each member.

The main advantage of this dataset is that it provides insight into user behaviour and opinions whilst providing exact measurements of kilometres driven unaffected by the self-reporting bias.

3.2 Dependant variable

The dependent variable is kilometres driven by each member's account, as provided by Autonapůl. Kilometres driven are precisely measured (not self-reported) mileage on the vehicle's odometer, which App users use. The information from the odometer is sent in real-time to a database of Autonapůl company. The kilometres driven were provided for the last year before the questionnaire was collected. This value had to be adjusted because some users had their membership for less than a year, and some even less than a month.

The dependent variable was calculated as follows:

$$km\_monthly = \begin{cases} \frac{km\_year}{months\_membership}, & \text{if } months\_membership < 12 \\ \frac{km\_year}{12}, & \text{if } months\_membership \geq 12 \end{cases}$$

3.2.1 Outliers

From the out *km_monthly* variable, dropping both outliers at the 99th and 95th percentile was considered. At the 99th percentile, the break-off point is 850 kilometres per month, leading to 4 outliers and at the 95th percentile, outliers are over 490 kilometres per month, leading to 15 outliers. After comparing models with each option and qualitative analysis of each potential outlier observation, we decided not to remove any as the members did not have any unusual characteristics compared to the rest of the sample, e.g. a larger number of drivers using the same membership account.

3.3 Independant variables

Independent variables available from the questionnaire were chosen from the literature review, mainly from papers modelling vehicle miles travelled Cervero *et al.* (2007); Jung & Koo (2018). Furthermore, descriptive statistics in the report from Zvěřinová *et al.* (2017) were used to determine these predictors. As a result, both car-sharing-related and socio-demographic variables were used. Explanatory variables came from both databases. From the following, the information about where a subscriber lives and the length of membership is part of a database that Autonapůl provides. All other explanatory variables were gathered via the original survey.

3.3.1 Socio-demographic variables

Age is a factor shown to affect the kilometres driven (Cervero *et al.* 2007). Within our dataset, the mean and median of the age of respondents is in line with the literature review findings.

We define *income* as the midpoint of the interval shown in the questionnaire. *Income* was defined as zero for those who did not want to provide this information. To account for potential patterns underlying an individual's decision to withhold income information, a binary variable named *income_missing* was generated.

3.3.2 Car-sharing related variables

The variable *months_membership* is directly provided by Autonapůl and takes values from 0 to 171. To differentiate between newer and older members more effectively, a binary variable called *new_member* was introduced. This variable is assigned a value of 1 when the *months_membership* is less than or equal to 3 and assigned 0 otherwise.

Leisure is a binary variable equal to 1 when a member's most frequent use of the service is for vacation, trip and hobby purposes and 0 otherwise. Participants who use the service less than 12 times per year were asked about their last trip purpose rather than their most common one. Therefore, the value of this variable was then determined based on this response.

Another response was collected via a scale on the question, "How likely are you to recommend Autonapŭl to your friends, colleagues, or acquaintances?". Respondents were picked from a scale of 1 (definitely would not recommend) and 10 (definitely would recommend), from which the Net promoter score (NPS) of a firm is usually calculated. Based on the rules of NPS grading, respondents with 9 or 10 were assigned 1 for the *nps_promoter* dummy variable.

Variable $many\_drivers$ is a dummy equal to one if three or more household members use the same membership account on zero otherwise. As each person might use the service with different intensities, we cannot include this number of drivers in the dependent variable as we did in the case of $months\_membership$ or as a continuous variable into the regressions. Therefore, it was included as a dummy independent one.

Autonaůl provided us with information about the city of registration for all 642 members. Of the 9 cities, Prague and Brno were the most frequent, with 273 and 264 out of all members registered to drive there, respectively. Therefore, two dummy variables were generated named *prague* and *brno* and the members from the remaining cities were left with zero for both to prevent the dummy variable trap.

Lastly, the variables $frequency\_high$ and $frequency\_low$ represent the respondent's rate of using the service as a driver and passenger. $frequency\_high$ is equal to 1 if they drive once a week or more, and $frequency\_low$ is equal to one if they drive less than once a month down to driving never. Respondents who drive at the frequency at a level which is something in between, were assigned 0 for both of these variables. Because the variables are correlated with the dependent variable $km\_monthly$, they will not be included in the main regressions to prevent endogeneity. However, a separate model was predicted using these variables solely as independent to examine the driving behaviour of each frequency level group.

3.3.3 Descriptive statistics

Descriptive statistics of all variables used in this thesis are listed in tables 3.1 and 3.2 and are reported either for all users (N=642), respondents (N=308) or those who did not participate (N=334).

Table 3.1: Descriptive statistics of continuous variables

Variable	N	Mean	Median	SD	Min	Max
km_monthly						
Users	642	118.10	46.83	178.90	0.00	1606.30
Respondents	308	154.19	82.33	185.72	0.00	1068.08
Did not participate	334	84.81	15.70	165.81	0.00	1606.30
months_membership						
Users	642	22.15	16.00	22.22	0.00	172.00
Respondents	308	22.28	16.00	23.22	0.00	172.00
Did not participate	334	22.03	16.00	21.28	0.00	171.00
age	308	36.50	35.00	8.25	19.00	72.00

Table 3.2: Descriptive statistics of binary variables

Variable	N	Frequency	Share (%)
notzerokm			
Users	642	493	76.79
Responents	308	275	89.29
Did not participate	334	218	65.27
new_member	642	85	13.24
prague	642	273	42.52
brno	642	264	41.12
married	308	145	47.70
children	308	128	42.11
university	308	241	79.28
employed	308	281	92.43
income_missing	308	71	23.36
car	308	90	29.61
centre	308	208	68.42
many_drivers	308	34	11.04
nps_promoter	308	211	69.41
leisure	308	114	37.50
frequency_high	308	32	10.39
frequency_low	308	138	44.81

Chapter 4

Methodology

4.1 Comparing respondents vs. those who did not participate

4.1.1 Kilometres driven

Due to voluntary participation in the questionnaire, uncertainty exists regarding the potential influence of self-selection bias on the collected data. Individuals who were willing to answer to the questionnaire (respondents) might exhibit higher levels of satisfaction with the service and, consequently, may utilise it more frequently than those who did not participate in the survey. A two-sample t-test with equal variances was conducted to examine these expectations to compare the mean monthly kilometres driven between the two groups.

Table 4.1: Two-Sample t-test: respondents vs. those who did not participate in the survey

Respondent	**Observations**	**Mean (Std. Err.)**
0	334	84.81 (9.07)
1	308	154.19 (10.58)
Combined	642	118.10 (7.06)
Difference		-69.37 (13.88)

Users who participated in the survey used a shared car more than the users who did not participate in the survey, with a mean 154 km and 85 km a month, respectively. We reject the null about the equality of the two means at any convenient level (p=0.000). Therefore, the difference of approximately 66 kilometres in means is statistically significant.

We investigated the users who did not use the App last year ("passive users"). The following table displays their representation against those who have driven any positive number of kilometres during the last year ("active users") in the groups of respondents, those who did not participate in the survey and all members.

Table 4.2: Description of *zerokm*

zerokm	**Users (%)**	**Respondents (%)**	**Did not participate (%)**
0	493 (76.79)	275 (89.29)	218 (65.27)
1	149 (23.21)	33 (10.71)	116 (34.73)
Total	642	308	334

About 23% users did not use the App during last 12 months. The share of passive users is smaller among the survey participants (11%) than in the group of users who did not participate in the survey (35%).

Due to the differences in the proportions of zero observations between respondents and those users who did not participate in the survey, an additional t-test with equal variances was conducted with excluded observations of zero kilometres. The following table displays the results.

Table 4.3: Two-sample t-test: respondents vs. those who did not participate in the survey (active users)

Respondent	**Observations**	**Mean (Std. Err.)**
0	218	129.95 (12.90)
1	275	172.69 (11.35)
Combined	493	153.79 (8.57)
Difference		-42.75 (17.16)

Users who participated in the survey used a share car more than the users who did not participate the survey, with the mean 173 km, and 130 km a month, respectively. The corresponding p-value for the alternative hypothesis is higher at 0.0131, and the difference between means is lower at approximately 43 kilometres. However, we still reject the null hypothesis that the means are equal.

In summary, both t-tests provide strong evidence to suggest a significant difference in the means between the two groups being compared.

4.1.2 Survey participantion

A Probit model was employed to assess the impact of additional kilometres on completing the questionnaire. The dependent binary variable is defined by participating in and completing the survey (=1). The explanatory variables include *prague*, *brno* and *months_membership* as they are also available for all members to assess their relationship.

Table 4.4: Estimation of *questionnaire*

Probit	Marginal effects (Robust SE)
km_monthly	0.0006***
	(0.0002)
months_membership	-0.0001
	(0.0010)
prague	-0.1898***
	(0.0563)
brno	-0.1447**
	(0.0595)
Observations	642

Note: *p < 0.1; **p < 0.05; ***p < 0.01.

The results indicate that the probability of participating in the survey increases by 0.05% for each additional kilometre driven per month. This association with kilometres driven is statistically significant at any convenient level (p-value = 0.000). This further suggests that the decision to fill out the questionnaire was unlikely to be due to random chance. Furthermore, members from Prague and Brno were less likely to respond to the questionnaire than those from other cities, with marginal effects of -19% and -14%, respectively. The length of the membership does not have a significant effect on responding to the questionnaire.

Due to the differences between the group of respondents and non-respondents highlighted above, we cannot generalise the conclusions deducted from the questionnaire data collected on respondents on the whole population of Autonapůl car-sharing members.

4.2 Selectivity problem

Among all respondents, 33 (10,7%) did not drive with the Autonapůl car-sharing service during the last twelve months. Explanations for this behaviour can be divided into two main groups. Either they are otherwise active in other than observed months. Or the absence of kilometres could indicate that the user has recently signed up and has no intention to use the service or is done using it altogether.

This may cause the problem of selectivity, which poses a challenge when employing traditional ordinary least squares (OLS) on all 308 observations, as it could lead to biased estimates. Therefore, it's necessary to use a treatment method to address this issue.

Numerous treatment methods are available for the selectivity problem in the single-equation demand model, and Smutna & Scasny (2017) evaluated many of them in their paper. Smutna & Scasny (2017) ranked the methods in categories according to a reason why zero consumption might appear and be reported. They then apply these methods to different food consumption items with different shares of zeros. In our case, the selectivity problem arises from users who did not drive any kilometres within the observed period. Our sample, with 10,7% of zeros, lies between low and moderate levels of censoring from the paper. Corresponding best suitable methods are the sample selection model with Cosslett's semi-parametric estimator, the Two-part model and Heckman's two-step estimator.

Within all levels of censoring, the Heckman two-step estimator performed very closely to Cosslett's semi-parametric estimator. Thus, in this thesis, only the Heckman two-step will be used. The two-part model also gives similar results to Heckman's two-step estimator in the lower levels of censoring and will also used.

4.2.1 Heckman two-step model

The Heckman two-step sample correction method consists of two stages (Heckman 1976).

In the first stage, a participation equation is estimated, in our case, using a probit model.

$$y_1^* = X_1\beta_1 + u \tag{4.1}$$

The y_1^* denotes a dependent variable, in our case binary *nonzerokm*, which equals 1 if a person participates and 0 if not. X_1 denotes the matrix of regressors which influence this decision.

The inverse Mills ratio (IMR) is then derived from the participation equation. The IMR is defined as the ratio of the standard normal density of y_1^* named ϕ and the standard normal cumulative distribution function Φ.

$$IMR(\widehat{y_1^*}) = \frac{\phi(\widehat{y_1^*})}{\Phi(\widehat{y_1^*})}, \widehat{y_1^*} \in R \tag{4.2}$$

This correction term captures the selection bias and helps to obtain consistent and unbiased parameter estimates.

In the second stage, as the outcome equation, a regression model is estimated using the IMR as an additional independent variable.

$$y_2^* = X_2\beta_2 + IMR(\widehat{y_1^*}) + v, y_2^* > 0 \tag{4.3}$$

y_2^* corresponds to dependent variable *km_monthly*, with the condition that it has positive values, and X_2 denotes the matrix of regressors, which affects the number of kilometres driven.

In order to achieve reliable results with the Heckman two-step method, it is essential to have distinct sets of independent variables, denoted as X_1 and X_2. Except for the IMR variable, the Heckman model would experience perfect collinearity in its independent variables if these sets were identical. However, even the IMR is created with the covariates from the participation equation.

Therefore, to avoid collinearity, it is necessary not to include at least one of the regressors from the participation equation in the outcome equation. In our case, this variable is *new_member* because new members, likely in the early stages of their engagement, may use the service later. This variable is unsuitable for the outcome equation, as the dependent variable *km_monthly* is also calculated from *months_membership*, which partly adjusts for this effect.

Furthermore, some variables were determined not to be suitable for the probit regression due to endogeneity with *notzerokm*. These variables are *many_drivers*, *leisure* and *nps_promoter* and are used just in the outcome equation, where the problem witch endogeneity with *km_mothly* does not persist.

4.2.2 Two-part model

The two-part model is a method to treat limitations in the dependent variable. This variable has a lower bound, in our case zero, which occurs in a significant number of observations. The model consists of two parts, which focus on different data characteristics. Compared to the Heckman two-step model, the participation and the outcome are modelled separately.

The first part addresses the zero values by employing a model that estimates the likelihood of obtaining a positive result compared to a zero value otherwise. This will be a probit model same as the Participation equation in the Heckman two-step model 4.1.

The second part, the OLS model, then focuses only on the positive values, excluding observations that have zero kilometres driven. This exclusion removes 33 observations from our sample.

$$y_3^* = X_3\beta_3 + w, y_3^* > 0 \tag{4.4}$$

In this model, y_3^* also corresponds to dependent variable *km_monthly* with the condition that it has positive values, and X_3 denotes the matrix of regressors, which affects the number of kilometres driven.

Chapter 5

Results and disscussion

5.1 Frequency association with milleage

Car-sharing is typically used by different types of users who may differ by their residence, frequency of usage, purpose of the trip, and others. Let us first investigate whether mileage driven by shared vehicles differs across different car-sharing usage frequencies. We have split respondents into three groups based on whether they use the service multiple times a week, multiple times a month or less than once every month using variables $frequency\_high$ and $frequency\_low$. In table 5.1, there are results of a regression performed.

The middle group, who use the App at least once a month but less often than every week, drives on average 200 kilometres monthly. Respondents from the group with a higher frequency of use, who use the service at least once a week, drive on average 395 kilometres monthly. Respondents with low frequency of App use, who used the App lees than once a moth, drive on average 53 km a month only, one eight of the milleage of the respondents with high frequency.

5.2 Modelling usage of the App

5.2.1 Model interpretation

In this subsection, we present the results from a probit model that aims to analyse the factors influencing whether a respondent drove any kilometres within the last year. The table 5.2 provides an overview of the results of the performed probit model having *notzerokm* as its dependent variable, including the marginal effects and robust standard errors for each independent variable.

Table 5.1: Relationship between frequency and *km_monthly*

	Estim. Coeff. (Robust SE)
frequency_high	195.6691***
	(47.3940)
frequency_low	-146.5109***
	(16.2514)
constant	199.5041***
	(14.8833)
Observations	308

*p < 0.1; **p < 0.05; ***p < 0.01

Only two variables have been shown to affect the variable *notzerokm* significantly and that is at any convenient level.

Firstly, for car owners, there is approximately 13% reduced probability that they have driven any kilometre during the last year. The negative sign of this effect is in line with previous research. Either a person started using car-sharing as a second or third vehicle, and therefore, it is necessary just occasionally. Alternatively, car-sharing served as a gateway towards car usage. After using the service for some time, the member decided to purchase their vehicle and reduce their car-sharing usage (Giesel & Nobis 2016). We cannot prove or reject this conjecture on our cross-section data and thus this remains for future research.

Secondly, being a subscriber for less than 3 months is positively associated with not using the App, i.e. zero km driven for last twelve months. It has a marginal effect of -0.14, implying that with a new member, there is a reduced chance that they have yet to drive any kilometres by 14%. A possible explanation is that people register further before they start using the service, or they register and afterwards change their minds and do not intend to use it. However, the latter effect would be present also with the longer-standing but passive members.

Other selected socio-demographical variables do not significantly affect the probability of actively participating in the service. The marginal effects of variables *married*, *employed*, and *centre* have a positive sign, and the remaining variables *age*, *children*, *university* and have a negative marginal effect. Comparing signs to the reviewed literature on the frequency and quantity of kilometres driven, they are as anticipated except for *income*, as more disposable income was previously shown to lead to more kilometres driven (Ceccato & Diana 2021; Becker *et al.* 2017b; Giesel & Nobis 2016).

Table 5.2: Participation equation for *notzerokm* (probit model)

	Marginal effects (Robust SE)
age	-0.0013
	(0.0021)
married	0.0225
	(0.0349)
children	-0.0250
	(0.0365)
university	-0.0205
	(0.0328)
employed	0.0361
	(0.0717)
income_missing	-0.0360
	(0.0583)
car	-0.1270***
	(0.0443)
centre	0.0456
	(0.0348)
new_member	-0.1360***
	(0.0627)
Observations	308

*p < 0.1; **p < 0.05; ***p < 0.01.

The performed analysis has its limitations. There are likely unobserved variables that affect the behaviour of car-sharing members, which are difficult to predict or collect data on and incorporate into the model. These unobserved factors may lead to omitted variable bias and influence the estimated coefficients. Therefore, while the probit model provides valuable insights, it is important to acknowledge the limitations of this analysis and consider the potential impact of unobserved variables and selection bias caused by pasive users on the results.

5.3 Modelling kilometres driven

This section presents the results from three different models examining the relationship between numerous socio-demographic and car-sharing-related independent variables on *km_monthly*. The models employed are Ordinary Least Squares (OLS) and two sample-selection correction methods, the Heckman two-step and Two-part models. The table 5.3 summarises the regression results for each model.

The Akaike information criterion (AIC), Bayesian information criterion (BIC) scores, and Log-Likelihood values were observed to compare the three models in this thesis.[1]

When comparing the Heckman two-step and Two-part models, each can be determined to be better depending on the goodness of fit measure. Heckman two-step has a better AIC score and Log-likelihood value. However, when comparing BIC, the Two-part model is the best-performing one.

The Heckman two-step and Two-part models provide a more comprehensive approach by addressing selectivity bias and incorporating a better trade-off between goodness of fit and model complexity, as reflected in their lower AIC and BIC scores.

Another factor that can be considered when further comparing the Heckman two-step and Two-part models is that the IMR is insignificant in the Heckman two-step model. This suggests that the selectivity bias correction may not substantially affect the estimated coefficients and overall model fit. In other words, reasons for not driving any kilometres might be based on random unobserved factors which do not further influence the demand for kilometres with other respondents and thus make the participation model not well-performing.

All models show that *age* is a significant determinant. With increasing age, respondents drive more. However, in there are not many elderly people in the sample, and we would expect this effect to decline at the age of retirement, which would be noticeable if we had more observations of them.

The variable *children* is also significant in all three models, indicating its consistent positive influence on car-sharing usage. This suggests that individuals with children are more likely to utilise car-sharing services, which goes against our findings from the literature review, e.g. Ceccato & Diana (2021); Becker *et al.* (2017c). However, the presence of children may increase the need for flexible and comfortable transportation options, leading to a higher demand for car-sharing.

[1] Smutna & Scasny (2017) use the same goodness of fit measures in their paper on the problem of selectivity from which we took inspiration for the methodology of this thesis.

They found their OLS models performing far worse than the rest. The same is observed with our three models. OLS model has much worse AIC, BIC scores and Log-Likelihood values than the two models which treat the selectivity issue.

Variable *car* is another significant determinant of *km_monthly*. Respondents who own a car drive less than the others, which aligns with our expectations and literature review in which we explained how private cars and car-sharing behave as substitutes. Car owners probably utilise car-sharing as a second or third vehicle for the household.

A factor having a significant positive effect on *km_monthly* is *many_drivers*. Respondents whose member account is utilised by three or more people in their household drive on this account over 100 kilometres more per month than the rest.

The significance of *nps_promoter* as a positive determinant gives us valuable information about the respondents. Those who use the service more are satisfied with it to the extent that they recommend it to others, which is a sign of overall well-functioning service.

The last significant variable is *leisure*. Respondents who use the service for activities in their free time tend to drive more distance. This could be because these trips are longer than trips for necessities. As one of the possible goals of the company is to make people increase their kilometres driven to make gain higher profits, this finding can be used for further service marketing purposes.

The socio-demographic variables *married*, *university*, *employed*, *income* and *centre* are insignificant in all models. Other factors related to transportation needs not captured by our dataset may have a more substantial impact.

Some limitations arise from the nature of the dataset. Even though it has significant benefits of combining revealed data from the company with the questionnaire, it has its drawbacks. Members who filled out the questionnaire behaved differently, as discussed in section 4.1, which causes self-selection bias. Therefore, the finding might not represent the whole population of members and in future research, a larger sample of all members would be more telling.

Furthermore, the models used in this study display heteroskedasticity, which has been addressed by employing robust standard errors. However, this suggests that the models may not best fit the variable *km_monthly*. Unfortunately, we could not develop a more suitable solution with the available dataset. A larger dataset with more detailed information would offer a better foundation for further research on car-sharing usage determinants. Nonetheless, accurately capturing all the influential variables when modelling human behaviour can still pose challenges.

Table 5.3: Regression results for *km_monthly*

	OLS Estim. Coeff. (Robust SE)	**Heckman two-step** Estim. Coeff. (Robust SE)	**Two-part** Estim. Coeff. (Robust SE)
age	2.7228**	2.7197*	3.1443**
	(1.2585)	(1.4099)	(1.3464)
married	4.0700	0.2643	-7.5703
	(22.4864)	(22.1543)	(23.1387)
children	37.6303	47.0564*	55.3073**
	(26.4034)	(27.2941)	(28.0199)
university	-25.7911	-40.7938	-31.2920
	(24.0803)	(26.7371)	(25.4716)
employed	38.6734	64.1510	42.3800
	(43.6649)	(43.2617)	(48.7068)
income	-0.0001	-0.0003	-0.0002
	(0.0005)	(0.0005)	(0.0005)
income_missing	24.5686	31.2109	44.8544
	(36.0784)	(38.1335)	(39.1564)
car	-66.0352***	-103.9890**	-48.6338**
	(21.2521)	(39.1255)	(23.2256)
centre	26.7349	38.8574	18.9671
	(24.4707)	(29.3942)	(25.4665)
many_drivers	110.9296**	135.5559**	126.7888**
	(51.2657)	(52.8539)	(52.6784)
nps_promoter	64.8793***	61.5641***	63.5954***
	(21.5661)	(23.6680)	(23.9459)
leisure	69.1205***	93.6912***	86.2936***
	(20.3638)	(20.8392)	(20.9490)
IMR	—	278.2539	—
	—	(183.1639)	—
constant	-48.97722	-96.3795	-61.6096
	(67.4083)	(68.3011)	(73.0655)
Observations	308	275	275
AIC	4061.5290	3627.2380	3628.5330
BIC	4110.0200	3677.8730	3675.5510
Log-Likelihood	-1863.7644	-1662.1190	-1663.7663

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Chapter 6

Conclusion

This thesis examined car-sharing usage determinants using ordinary least squares (OLS), Heckman two-step, and Two-part models. Through the analysis, we identified significant variables that influence the use of car-sharing services. Additionally, the effect of frequency of use on kilometres driven was examined using OLS. The analysis was performed on a sample of respondents to a survey, who in general, drive more than those who did not participate in the survey.

Firstly, age, having children and car ownership were identified as significant socio-demographic factors in car-sharing usage. The positive coefficients for *age* and *children* indicate that as age increases and with the presence of children in the household, respondents use the car-sharing service more. Moreover, the negative relationship between *car* and *km_monthly* supports the existing literature on the relationship between car-sharing and car ownership.

The Heckman two-step and Two-part models, with lower AIC and BIC values, provided a better fit for the data than the OLS model on all respondent observations. These models accounted for selection biases resulting in improved model performance.

It is essential to acknowledge the limitations of this study. Our analysis was based on a dataset, which has the advantage of providing precise information on kilometres travelled. However, it can still suffer from self-reporting biases or limitations, affecting the generalizability of the findings. The Main recognised downside is the small size of the dataset and having just a part of the member community filling out the questionnaire. Additionally, the complex nature of human behaviour introduces challenges in capturing all influential variables accurately.

Future studies could benefit from larger datasets with more detailed information to further advance research on the determinants of car-sharing. Additionally, incorporating qualitative research methods, such as interviews or surveys, may provide deeper insights into the motivations and preferences of car-sharing users.

In conclusion, this thesis contributes to existing research on car-sharing, which focuses mainly on modal changes of this nuance service, whilst this thesis aims to gain insight into factors influencing individuals car-sharing usage. These findings are beneficial for the service provider to understand its customers and make informed decisions to promote this service which has been shown in the literature review to be a sustainable alternative to private vehicle ownership.

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