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# Using longitudinal data to understand the impact of car sharing on car ownership: An analysis based on the German Mobility Panel (MOP)


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# Abstract

Car sharing is a shared mobility service that allows renting a car for a short time or distance without the burden of complete ownership, such as maintenance, insurance, and repair responsibilities. Car sharing, as one of the newest additions to transportation modes, has the potential to attract a significant number of drivers. In recent decades, academia and government have increasingly paid attention to car sharing and how it affects the urban transportation system. One of the most important indicators for evaluating car sharing benefits is its impact on household car ownership.

Although the effects of car sharing on household vehicle holdings have been extensively studied, there is a lack of dynamic analysis through a panel survey, despite the fact that the effects of car sharing on car ownership is a dynamic process that takes place over time. In this study, we perform the analysis using data from the 2012-2020 German Mobility Panel (MOP), an unbalanced and rotating panel survey conducted annually since 1994. All the German-speaking households living in Germany can voluntarily participate. The MOP sample size is provided in two household and person levels, with 1173 households and 1913 individuals in 2012. It then recorded 80% growth, reaching 3461 individuals in 2020. Noticeably, the sampling method is rotating, and three years of information are the maximum available data for each interviewee.

This thesis aims at understanding the impact of car sharing on car ownership, and it investigates in light of early studies' limitations, such as casualty effects, self-selection, and recall biases. This analysis uses longitudinal panel data to prevent recall bias. Moreover, propensity-score-based matching is used to help control self-selection bias due to differences in observed socio-demographic characteristics between respondents. The treatment and control groups are identified to isolate car sharing membership effect and establish causal relationships. It is noted that control groups contain never car sharing members. We select the nearest neighbor matching method with a ratio of five for this thesis. Both control and treated units are estimated using logistic regression using R software.

We identify the treated group for each wave of the MOP survey, finding that 115 unique car sharing members with at least one year of information fit the dynamic analysis purpose. Having paid attention to the dynamic behavior, among 5 members showing an increasing trend in their car holdings, 3 bought a new car in the same year of unsubscription to a car sharing program. In addition, 5 out of 6 members sold a car when they subscribed to a car sharing scheme.

Afterward, we found 676 unique matched IDs by performing the matching method. With car ownership patterns of all the treated and control units, it is then possible to perform a matched-pair comparison. In both groups, most units do not change their car ownership. 4.7% of the control groups purchased a new car, but 4.3% of the treated ones. Oppositely, more car sharing users foregone a vehicle than the controls, amounting to 5.2% and 4%.

Although such results are based on a small number of observations related to car ownership changes of car sharing members, we finally project them to the whole universe (German car drivers) to show that car sharing subscription and unsubscription versus car ownership changes are not represented by symmetric patterns, therefore cross-sectional data fail in understanding the real impact of car sharing on car ownership.

*Keywords: car sharing, car ownership, propensity score matching, panel study, MOP, Germany.*

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# Chapter 1: INTRODUCTION

Cars are one of the most commonly used mobility types in society. Convenience and ease, travel time, flexibility, and status symbol are the main reasons people use cars, as well as two underlying influences which are undeniably important, one is habit and the second one is the availability of alternatives.

Although private cars have many benefits, drawbacks also exist. In recent years, shared mobility schemes have received significant interest from transport planners, researchers, and policymakers to seek more energy-efficient ways to meet daily transportation needs for those market segments not easily captured by public transport or active means (walk, bicycle). This interest also came from the challenges communities face from the continued growth of vehicle ownership and usage, along with the associated consequences such as increased traffic congestion, parking issues, resource usage, and air pollution.

Car sharing is one of the shared mobility services that can potentially cause a reduction both in private car usage and car ownership, and encourage people to use alternative modes of transport, e.g., bus, train, walking, cycling, etc. (Martin and Shaheen, 2011). Car sharing is like car rental when an individual can use a vehicle for a short distance or time. Members can pay for a shared-vehicle fleet on a per-hour and per-mile/kilometer basis. It allows users to take advantage of a private vehicle without the burden of complete ownership, such as maintenance, insurance, and repair responsibilities.

The car sharing program facilitates both an increase and decrease in vehicle use by individuals. It can increase by gaining auto access for low-income households when owning a private car is not affordable. Thus carless households also would be able to drive through car sharing in today's highly car-dependent societies (Litman, 2000). This alternative transport mode is beneficial for non-car owners. On the other hand, carsharing also facilitates a decrease in auto use by allowing households that own cars to obtain automobile access through shared vehicles alternatively. Such households can reduce their utility and shift to public transit and non-motorized modes of transportation. Therefore, due to fewer personal vehicles being needed, carsharing households often experience a reduction in travel and vehicle ownership. For many households, carsharing can either reduce or even eliminate the need for private vehicle ownership.

Additionally, car sharing benefits car owners who drive only occasionally, as well as carless households. For instance, as shown by Litman (2000) and Prettenthaler and Steininger (1999), in the U.S. and Austria, vehicle owners who drive less than 10,000 km (15% of vehicles) or 15,000 km (69% of households) per year are better off switching to car sharing. The advantages are not only limited to personal car sharing users. Sharing cars increases the average daily usage time per car and reduces the time spent stationary, resulting in fewer cars being needed to satisfy everyone's travel needs. Moreover, car sharing organizations usually use fuel-efficient or even electric vehicles, which are also environmentally friendly.

Among the main areas of research in car sharing, the study of its impact on personal vehicle ownership is one of the significant streams. Even though the effects of car sharing have been extensively studied (e.g., Martin and Shaheen, 2011; Martin et al., 2010; Huwer, 2004; Zhou et al., 2017), there are still several challenges. Firstly, Prior studies have typically relied on data from existing car sharing organizations or operators. Accordingly, all respondents were already car sharing members, and most did not own a vehicle (Martin et al., 2010). This is the situation where self-selection bias could arise when the car sharing members who self-select themselves into the group were found to have a higher awareness of the environment and willing to commit to more sustainable behaviors (Costain et al., 2012). As such, previous findings regarding the impact of car sharing on household vehicle ownership may have been overly optimistic, and there could be little or no effect on vehicle ownership by the general public as a result of car sharing programs. Secondly, a general lack of dynamic analysis in this study area could be reached by conducting a longitudinal survey. The majority of prior studies were based on cross-sectional surveys while monitoring private vehicle ownership for a consecutive period could show a different result.

This thesis aims to quantitatively investigate whether conventional car sharing programs significantly impact people’s car holding status and mobility behavior. To answer these questions, a longitudinal survey in Germany was used, since it is a rare example of a longitudinal panel survey in the transport sector where data are available upon request. The respondents were a sample of the general public in Germany rather than just members of car sharing organizations. The matching method has been employed to dynamically analyze the survey's nine waves (2012_2021) data.

The following chapter provides an overview of the relevant car sharing literature. Chapter 3 presents the experimental setting, data set description and characteristics. Then, the analytical methodology and data preparation are discussed in chapter 4. Fifth chapter describes the descriptive and quantitative analysis and the results, respectively. Finally, the thesis concludes with chapter 6 summarizing and discussing the main findings.

# Chapter 2: LITERATURE REVIEW ON THE IMPACT OF CAR SHARING ON CAR OWNERSHIP

Urban transportation systems are directly affected by car sharing in four main ways: the impact on household vehicle ownership, car usage, mode choice, and vehicle energy consumption and emissions. The most important indicator for evaluating car sharing benefits is its impact on household car ownership. Researchers have devoted a great deal of attention to this study area, as it also plays a significant role in government decisions to promote car sharing development. This section discusses corresponding topics with more significant details, starting with early studies about car sharing impacts on vehicle ownership levels after a general overview of the literature on car sharing, followed by the limitations of earlier studies in this research area. Then methodological advances are discussed in detail, and finally, a summary of the result concludes this section.

Car sharing was firstly introduced in Switzerland at the end of the 1940s (Becker et al., 2017), which opened in 1948. Other attempts to establish a car sharing program in European countries continued in subsequent decades, including France, starting in 1971, Netherland, which opened in 1973, various places in Britain in the late 1970s, and Sweden, opening in 1983. The current form of car sharing has its roots in Switzerland and Germany, where programs date back to the late 1980s (Millard-Ball, 2005). Car sharing has only become increasingly common in urban areas in recent years (Clewlow, 2016; Ferrero et al., 2018; Namazu and Dowlatabadi, 2018; Shaheen and Cohen, 2007), when larger players from the automotive sector started entering into the market.

Through car sharing, fixed costs are transformed into usage fees, which completely change driving economics (Cohen and Shaheen, 2016). A household owning a car pays very little for each additional trip since car payments, insurance, and taxes have already been incurred. However, a strong financial incentive to drive less is provided by the cost of car sharing directly proportional to the amount members drive. Users might choose their travel mode more rationally by being more aware of the actual costs of transport alternatives (Cervero et al., 2007; Cervero and Tsai, 2004). Furthermore, car sharing can enable households to sell their owned or a second or third vehicle by providing access to a car for their occasional trips. Therefore, car sharing could influence mobility behavior and travel habits and positively impact the environment (Ceccato and Diana, 2021; Chicco and Diana, 2021; Lane, 2005; Shaheen and Cohen, 2012).

Car sharing is of the newest additions to transportation modes, which can potentially change individuals' relationships with the car in dense, urban communities. A car sharing program can positively or negatively impact mobility and the environment (Baum et al., 2012), which is also true for its impact on private vehicle ownership. Car sharing may result in car owners shedding their cars, but it is also conceivable to lead them to buy cars, especially for households without private cars or one-car holders. Moreover, by expanding access to automobiles, car sharing could encourage motorized travel, especially among car-less members who are used to public transportation, cycling, and walking (Diana and Ceccato, 2022; Martin et al., 2010; Cervero et al., 2002a). Therefore, it is believed that car sharing impacts on car ownership are needed to be thoroughly investigated.

## 2.1 Earlier studies

Car sharing was introduced and developed early in Europe and North America, so most related research was conducted there. A summary of 30 studies on how carsharing affects car ownership before 2005, 15 in Europe and 15 in North America, was published by Millard-Ball (2005) and found that in Europe, 22% of users sold their cars because of carsharing, 22% abandoned the purchase of a private vehicle, and each carsharing vehicle replaced four private cars. In North America, 20% of users sold vehicles due to carsharing, 41% gave up on purchases, and each carsharing vehicle replaced five cars. As part of the study, Millard-Ball also surveyed 1,340 car sharing members in North America to find that 11.3% of users would sell their cars, and 49.6% would sell their household's second car because of car sharing. The research also found that 70.5% of users would postpone buying a car and that each carsharing vehicle replaces 14.9 private vehicles. In another study, Loose summarized the development of car sharing in Europe in 2010 (Loose, 2010). It was estimated through a survey on 34 car sharing operators, resulting each car sharing vehicle substituted for an average of seven private vehicles.

In the North American studies, according to Cervero and Tsai (2004), which was one early study, about 29.1% of San Francisco carshare users shed at least one personal vehicle after carsharing participation, while about 67.5% expressed the intention to forego buying cars in the future. Each car sharing vehicle substituted for 6.8 cars. Later, Martin and Shaheen surveyed 6,281 members in 10 car sharing operators in North America (Martin et al., 2010), finding that 22% of members sold their cars, and 25% of the members foregone a purchase, all because of their subscription in a car sharing service. This has resulted in a conclusion of one car sharing vehicle replacing between 9 to 13 private vehicles. Around five years later, these two researchers surveyed 7,346 Car2go members in five cities in North America (Martin and Shaheen, 2016). They found that two to five percent of the Car2go population sold a car due to their membership, and every Car2go vehicle replaced between seven to eleven private vehicles.

In comparison between North American and European studies, Shaheen and Cohen (2007) studied round-trip-based car sharing programs, estimating that the number of private automobiles removed for every shared vehicle varied between 6 and 23 in North America and 4 and 10 in Europe. In Philadelphia, the number of private cars removed from the roads per shared vehicle designed for round-trips is estimated to be around 22.8, with 10.8 shed cars and 12 deferred car purchases (Lane, 2005), and 28.4 in London, representing a total of 8.6 cars removed and 19.8 avoided (Carplus, 2015). Notably, in a study in Netherland, car sharing replaced the second or third vehicle in other households (Nijland and van Meerkerk, 2017). They drafted a questionnaire and surveyed a sample of 140,000 individuals representative of the Dutch population, resulting in 363 car sharing respondents. This study aimed to estimate changes in mobility by asking participants about their level of car ownership at the current time and before subscribing to car sharing. It covered a period of one to three years for most respondents. Another study was focused only on free-floating services but in 11 European cities, with a sample of more than 10,000 survey respondents (Jochem et al., 2020). According to the results, a car sharing vehicle can optimistically replace up to twenty private vehicles, and a reduction in vehicle ownership was found in all 11 cities among FFCS members.

Although it is often believed that car sharing reduces car ownership in households, the impact of car sharing on car holding has been a debatable topic among authors because of its surprising results in some studies. Although Firnkorn and Müller (2011), who studied the early effects of FFCS on vehicle holdings in Ulm, Germany, found that the service had the potential to replace 19.2 private automobiles for every shared vehicle. On the other hand, after empirically exploring the impact of car sharing on noncorporate car ownership and car markets in 35 large German cities between 2012 and 2017, Kolleck (2021) provided a conclusion. The study showed no statistically significant relation between car ownership and free-floating car sharing and no significant impact of either type of car sharing on the markets for new cars and used cars. Car sharing does not significantly impact the desire for private cars (the impact is not large enough) and does not explain ownership reductions. Furthermore, several recent studies have shown that only a small number of the differences between users and non-users in car ownership and use can be attributed directly to car sharing (e.g., Mishra et al., 2015, 2019). These studies used data from 2011-2012 and focused on the San Francisco Bay Area with a sample size of 8299 survey respondents, including 241 car sharing users. Also, in 2017, approximately equal proportions of free-floating car sharers reported increasing and decreasing their usage of their vehicles since joining the service in a Swiss study (Becker et al., 2017).

There have been many uncertainties in this study area. Apart from being a car share user, the level of car ownership is also tied to many other subjective variables and attitudinal factors. For instance, those who are satisfied with the availability and the rental system of a car sharing service are more likely to shed the number of private vehicles owned (Kim et al., 2019; Ko et al., 2017; Schreier et al., 2018). The built environment is another variable, meaning that private cars can easily be substituted by other modes of transportation in some areas. According to Clewlow's research, members of car sharing living in dense urban neighborhoods own fewer cars than non-members, while suburban households own more cars (Clewlow, 2016).

## 2.2 Limitation of earlier studies

Some of the contrasting results that have been reviewed in the previous subsection are due to limitations in the research design. The study's limitations refer to those characteristics of design or methodology that impacted or influenced the interpretation of the results from the research. Limitations constraint the ability to generalize the study results to further applications. This section discusses some of these limitations of the studies on car sharing and its impact on car ownership.

### 2.2.1 Validation issues – Causality effects

Causality effect or cause-and-effect relationship is one of the key limitations of early studies. The concept of causal effect was officially introduced by Donald Rubin in 1976 (Rubin, 1976) and further explained by Rubin and Paul Rosenbaum in 1983 (Rosenbaum and Rubin, 1983) as well as Paul Holland in 1986 (Holland, 1986). Cause-and-effect is a relationship between two things, when something happens, it makes something else. In other words, the cause creates the effect. A cause is something that produces an event or condition, and effect is the result from that event or condition. Usually, in research, there are two types of variables. One is dependent, and another one is independent. A causal relationship or a cause-and-effect relationship between two variables means a change in the independent variable causes a change in the dependent variable. In car sharing and car ownership relation, car sharing membership is usually the independent variable, while the studies aim to find its impacts on car ownership (dependent variable).

Causal links between car sharing and car ownership imply a temporal sequence, with the treatment (carsharing enrollment) preceding the outcome (change in car ownership level). Thus, cross sectional data cannot prove causality but only help to generate some insights. Another kind of survey can be better solution. Moreover, the use of controlled study can be more effective to establish a causality relationship between car sharing and car ownership. In scientific studies, a control group is used to isolate an independent variable's effect to establish cause-and-effect relationships. The independent variable is changed in the treatment group but kept constant in the control group, then the two groups' results are compared. The more extensive coverage of this topic will be detailed in **Section 4.2**.

### 2.2.2 Validation issues – Biases

#### 2.2.2.1 Self-selection bias

Generally, self-selection occurs when respondents select themselves to be included in a survey or group. As a result, the sample may not be representative of the overall population. For example, the decision to participate in the study may be affected by some characteristics of the participants. In the context of carsharing, self-selection bias can be described as follows: The characteristics of people who choose to join car sharing may differ from those of non-members, concerning their socio-economic status, demographic background, and residential location preferences.

One of the common research designs in early studies was a cross-sectional study comparing members and non-members to evaluate car sharing's effects on car ownership. However, it also might be challenging to assess whether car sharing membership causes car ownership because self-selection could occur in such cases. Another widely used method was when subscribers are assumed to be the best candidates to judge how car sharing will affect their car ownership. In this case, car sharing's impact on vehicle ownership was overestimated in such studies focusing only on carsharing users' judgment. All because of the fact that car sharing subscribers who self-select themselves into the subscribers' group are found to be wealthier, more educated, more environmentally conscious, and people who are more open to social interactions and trying new products (Costain et al., 2012; Burkhardt and Millard-Ball, 2006; Rodier and Shaheen, 2003; Shaheen and Rodier, 2005). Thereby, such studies are biased.

As the first attempt to account for self-selection bias in carsharing, Mishra et al. (2015) identified more accurately the effect of car sharing on travel behavior by accounting for the potential predisposition toward enrolling in car sharing. Propensity-score-based matching was used in that study to control for self-selection bias due to differences in observed characteristics of respondents. In the end, the authors found that car sharing members significantly owned fewer vehicles than non-members with similar individual and household demographics, residential and job location characteristics.

#### 2.2.2.2 Recall bias

Recall or recollection bias occurs when people do not accurately remember previous events or experiences or subsequent events, and experiences may influence memories. In car sharing, data from car sharing operators and retrospective surveys are usually used in early studies about car sharing's impact on vehicle ownership. In fact, the study examined only car sharing users and compared the number of households' private vehicles before and after joining car sharing programs by directly asking them about current and past behavior. For instance, after surveying car sharing members in the U.S., Martin and Shaheen (2011) and Martin et al. (2010) observed that the number of vehicles owned by the 6,281 households surveyed decreased from 2,968 to 1,507. This reduction was also seen in the European context (Katzev, 2003), with declines of 44% and 60% reported by car sharing members in the Netherlands and Switzerland, respectively. Nevertheless, these results reflect the behavior of early adopters and not that of the general public due to self-selection bias (Heckman, 1977; Willis and Rosen, 1979; Rodier and Shaheen, 2003).

Similarly, many studies are based on cross-sectional surveys in which participants are asked about the number of their private vehicles multiple times (Registration time or one year before registration and survey time) (Namazu and Dowlatabadi, 2018; Nijland and van Meerkerk, 2017). Therefore, the results might be biased by respondents' memories. However, a limited number of studies are based on observed behaviors directly measured in multiple waves surveys, which are expected to produce less biased results (Becker et al.,2018; Cervero et al., 2007). Cervero and Tsai (2004) and Cervero et al. (2007) addressed recall bias by administering their survey to a panel in multiple waves. Moreover, constructing a control group was supposed to allow isolation of car sharing membership impact from other external effects.

### 2.2.3 Cross-sectional survey design

Most studies have used cross-sectional survey designs, which means that data were collected at a snapshot in time, e.g., Muheim and Reinhardt (1999), Lane (2005), Stasko et al. (2013), Giesel and Nobis (2016), etc. Another survey design used was a repeated cross-sectional in which a fresh sample is surveyed multiple times. For example, Cervero et al. (2007) conducted a study in San Francisco using repeated cross-sectional surveys in 2001, 2003, and 2005. They pointed out that since 2001, City CarShare members were 50% less likely than non-members to purchase a vehicle. Every 100 car sharing member households shed seven net vehicles, while in 100 non-member households, three net cars were added. This resulted in a 10-vehicle difference for every 100 families. However, cross-sectional data can have some limitations; for example, data are captured in a single time, and it cannot be definitive as a longitudinal type of data in establishing causal relationships (Kline, 2011, p. 98). Three main disadvantages of the cross-sectional studies are the weakness in analyzing behavior in a period of time, not being helpful to determine cause and effect relationships, and the timing of collection data not being guaranteed to be representative.

## 2.3 Methodological advances

Various methodological advances have been used to assess car sharing's impact on car ownership levels, and their advantages and disadvantages must be considered when reviewing the literature.

### 2.3.1 Longitudinal surveys, treatment and control groups

Since the drawbacks of the cross-sectional data became clear, it is now widely believed that the best approach to estimate the effects of any treatment is longitudinal panel data with randomized respondents in the treatment or control group (Rubin, 2008). Research with control groups helps ensure its internal validity. In your treatment group, you may see changes in your dependent variable over time. However, if there is no control group, it can be difficult to determine whether the change has arisen from the treatment.

Unlike cross-sectional surveys, longitudinal panel designs collect information on the same set of variables from the same sample members at two or more points in time. Evaluating the impact of car sharing on car ownership is a dynamic process in which changes over time are essential. The ideal is that the same group of individuals is followed during each survey wave. Therefore, it is possible to observe each person’s pattern over a period of time (Yee and Niemeier, 1996). It is also noted that being a car share user in the previous wave can affect an individual’s decision to purchase or sell any vehicle (Mishra et al., 2019). Statistical power and the advantage of estimating a greater range of conditional probabilities in a longitudinal analysis cannot be denied. These are the benefits that overcome a repeated cross-sectional study (Yee and Niemeier, 1996).

More recently, some investigations were conducted based on panel data, for instance, Haustein (2021) in which an online longitudinal survey was administered to DriveNow members and a sample of licensed drivers aged 18-65 years living in DriveNow's operational area who are considered potential car share users. The study was based on two surveys conducted over 2.5 years in Copenhagen of FFCS users (n = 776) and non-users (n = 720). Haustein found changing household composition between the first and second surveys was an important factor in their car ownership levels. In another study (Becker et al., 2018), the authors conducted a two-wave panel survey, six weeks and one year after the system lunch, estimating that by subscribing to a free-floating car sharing program, 6% of customers reduced their private vehicle ownership. Cohort one was drawn from members of the FFCS scheme, while cohort two was drawn randomly from the local driver's license population (control group). Lately, two interesting points have made Kolleck's (2021) investigation powerfully. This analysis was based on publicly available panel data from 2012, 2013, 2015, and 2017, and rather than relying on self-reports from users, they observed city-level changes in car sharing, linking these to ownership rates and registrations of new and used cars. It was an empirical assessment that potentially did not suffer from selection and recall biases and included rebound effects.

### 2.3.2 Differentiating impacts of distinct car sharing operational schemes

Another advancement in car sharing studies was about distinguishing car sharing impacts on different forms of car sharing. Car sharing has various schemes with different operational characteristics. Three main car sharing schemes are one-way free-floating (or free-floating car sharing, FFCS), one-way station-based, and roundtrip station-based (Shaheen et al., 2019). In some cases, operators offer combined services in which some cars are shared through fixed stations while others can only be used in an operational area. FFCS is the service when there is no need for an operational area/station and return trip, while in station-based car sharing, it is a must to pick up and return the vehicle to a parking area.

As was mentioned, the effects of car sharing on car ownership have been interesting for scholars, and the result of different car sharing schemes was also studied. For example, Beker et al. compared station-based and free-floating members in Basel, Switzerland, discovering that 19% of station-based and 8% of FFCS members foregone purchase a new car because of car sharing membership (Becker et al., 2017). Similarly, a study (Namazu and Dowlatabadi, 2018) in Canada was conducted to analyze the effects of car sharing on both roundtrip station-based and FFCS schemes. The authors found a reduction in the vehicle ownership rate of FFCS service from 1.08 vehicles per household to 0.98, and from 0.68 to 0.36 in the roundtrip station based. Thus, in contrast to free-floating carsharing, round-trip carsharing members were five times more likely to reduce their car ownership level. More recently, a study (Chicco et al., 2022) was conducted to compare car ownership reduction patterns among members registered in roundtrip station-based, free-floating, and combined services. They found that no matter which car sharing scheme, all users reported a lower level of vehicle ownership than the time before the subscription. However, roundtrip station-based subscribers are almost 15 times more likely to shed a vehicle than FFCS unique members. In this thesis, there is no difference between different schemes since they were not distinguished in the data set that is exploited in the following.

## 2.4 Summary of results

This section summarizes the important points found in the literature. In summary, car sharing has a spatially diverse and temporally dynamic impact on household car ownership. There will always be differences in research conclusions due to differences in countries, transportation systems, operation models, and research methods.

The following **Table 2.1** provides an overview of the discussed studies' results. The main points are detailed as follows:

- Cross-sectional and longitudinal survey

  Most of the studies are based on either cross-sectional surveys or repeated cross-sectional surveys. However, evaluating the car sharing impacts on household car ownership is a dynamic process focused on changes over time. Therefore, a longitudinal nine-wave data set at one-year intervals were used for this thesis in which an individual would potentially have participated in three waves.

- Comparing car sharing members and non-members

  In another group of studies, car sharing users and non-users were compared. It might be difficult to assess whether car sharing membership causes car ownership because self-selection could arise in such cases. In a study (Mishra et al., 2015), propensity-score-based matching was used to control for self-selection bias due to differences in observed characteristics of respondents. In this thesis also, propensity scored-based matching was used through the matching method with a large number of control variables. Moreover, like Cervero and Tsai (2004) the control group was used to allow isolation of the actual impact of car sharing membership from external effects. Finally, a random assignment of individuals in both treated and control groups was performed. One random member and non-member of each household was selected to be part of each treatment and control group.

- Retrospective survey

  Most studies that attempt to estimate the effect of car sharing are based on cross-sectional data comparing households' car ownership before and after membership with retrospective questions in a survey (e.g., Martin et al., 2010). In this study, a longitudinal setting was used to overcome limitations related to retrospective data, such as recall bias. There is a possibility that people's memories were blurred. By using longitudinal panel data, the survey respondents were asked only about their current travel behavior and socio-demographic characteristics. Through a before-and-after comparison with quantitative travel behavior data of both members and a control group, this thesis attempts to address such response biases.

- Consider only car sharing members

  Studies are divided into two, those in which car sharing non-members are also included in the survey and those considered only car sharing members or car sharing operators (e.g., Lane, 2005; Martin et al., 2010; Katzev, 2003). In the latter case, the problem is that data do not represent the general public. Therefore, the results cannot be generalized. Moreover, the results in these studies are potentially biased because of self-selection bias arising from members self-selecting themselves into a car sharing service. This thesis is based on the German Mobility Panel (MOP), which measures the mobility of people in Germany, i.e., the general travel behavior of people.

- Dropouts in longitudinal surveys

  Almost all the longitudinal studies suffer from dropouts. This is a longitudinal data set disadvantage and can occur for many reasons. In Haustein's (2021) study, they attempted to solve this problem by offering incentives for participation in later survey waves. However, this problem was not taken into consideration in this thesis, since field activities were not directly made but rather an existing survey dataset, i.e., the above-mentioned MOP, was exploited.

In summary, car sharing services have developed rapidly in recent years, and it is commonly believed that car sharing can generate vehicle ownership reduction benefits. Therefore, it is worthy of research to evaluate the effects. This thesis is based on a longitudinal publicity data set using propensity-score-based matching to control for self-selection bias due to differences in observed characteristics of respondents. Matching was performed between treated (car sharing members) and control groups (Never car sharing members) to allow isolation of the actual impact of car sharing membership from external effects. Notably, the approach was longitudinal panel data with randomized respondents in the treatment or control group to decrease the potential biases. Finally, as different car sharing schemes were not asked of respondents and were not distinguished in the data, they were not considered in this study.

**Table 2.1**
Studies investigating car sharing impacts on car ownership

| Literature | Location | Data | Respondents | Limitations | Main findings |
|---|---|---|---|---|---|
| Katzev (2003) | Portland, United States | Car sharing Portland | N=64 | Self-selection bias. Only Car sharing members are in the investigation. | Selling vehicles users: 26% Giving up purchasing vehicles: 53% |
| Cervero and Tsai (2004) | San Francisco, United States | Panel, paper survey and tracking. City CarShare | N=462 | The control group suffered from self-selection issues, probably biasing the results. | Selling vehicles users: 29.1% Giving up purchasing vehicles: 67.5% |
| Lane (2005) | Philadelphia | Cross-section, Online survey PhillyCarShare | Car sharing members N=262 | Only Car sharing members are in the investigation. Based on cross-sectional surveys. | Selling vehicles users: 24.5% Giving up purchasing vehicles: 29.1% |
| Cervero et al. (2007) | San Francisco, United States | Repeated cross-sectional survey (2001,2003 and 2005) City CarShare | Car sharing users and non-users, N=527 | Repeated cross-sectional surveys | Selling vehicles users: 24.2% |
| Martin et al. (2010) | North America | Cross-section, Online survey, late 2008. 10 organizations | Car sharing users, N=6281 | Self-selection bias. Based on cross-sectional surveys. Retrospective survey. Data only from existing car sharing organizations and contains only car sharing users. | Selling vehicles users: 22% Giving up purchasing vehicles: 25% |
| Firnkorn and Müller (2011) | Ulm, Germany | Cross-sectional survey, 2019 Car2go | 256 Prospective car sharing users and non-users (N=308) | Based on cross-sectional surveys. | Selling vehicles users: 3.8% Giving up purchasing vehicles: 9.7% Potential to replace 19.2 private cars for every shared vehicle. |
| Martin and Shaheen (2011) | North America | Cross-section, Online survey, late 2008. 11 organizations | Car sharing users, N=6281 | Self-selection bias. Only Car sharing members are in the investigation. | The number of vehicles owned by the 6,281 households surveyed decreased from 2,968 to 1,507 |
| Mishra et al. (2015), (2019) | San Francisco, United States | Cross-sectional survey | Car sharing users (N=241), Non-users (N=8299) | Based on cross-sectional surveys. | A small number of the differences between users and non-users in car ownership and use can be attributed directly to car sharing. |
| Martin and Shaheen (2016) | North America | Cross-section, Online survey. Car2go | Calgary (N=1246), San Diego (N=643), Seattle (N=2463), Vancouver (N=863), Washington D.C. (N=952) | Based on cross-sectional surveys. Self-evaluates of respondents about the impact of car sharing. | Selling vehicles users: 2-5% Giving up purchasing vehicles: 7-10% |

| Literature | Location | Data | Respondents | Limitations | Main findings |
|---|---|---|---|---|---|
| Nijland and van Meerkerk (2017) | Netherland | Cross-sectional survey, 2014 | Car sharing user N=363 | Recall bias.<br>Based on cross-sectional surveys. | Car sharing replaced the second or third vehicle in other households. |
| Becker et al. (2017) | Basel, Switzerland | Cross-section, Online survey | N=1480 | Based on cross-sectional surveys. | Approximately equal proportions of free-floating car sharers reported increasing and decreasing their usage of their vehicles since joining the service. |
| Namazu and Dowlatabadi (2018) | Vancouver, Canada | Cross-sectional survey<br><br>Modo<br>Car2go | Car sharing users (N=3040) | Recall bias.<br>Based on cross-sectional surveys.<br>Only Car sharing members are in the investigation. | Selling vehicles users Car2go:<br>12%<br>Selling vehicles users Modo:<br>35% |
| Becker et al. (2018) | Basel, Switzerland | Two-wave Panel survey, 6 weeks and 1 year after launch | Car sharing members and non-members (N=790) | - | By subscribing to an FFCS, 6% of customers reduced their private vehicle ownership. |
| Kolleck (2021) | Germany | Publicly available panel data from 2012, 2013, 2015, and 2017. | - | - | No statistically significant relation between car ownership and FFCS. |
| Haustein (2021) | Copenhagen, Denmark | online longitudinal survey,<br>2 times in 2.5 years<br><br>DriveNow | Car sharing users (N=776)<br>Non-users (N=720) | Dropout of participants. | Significant effect of joining FFCS on car ownership reduction, but after registration time. |
| Chicco et al. (2022) | Germany | Cross-sectional online survey | car sharing members (N=612) | Based on cross-sectional surveys.<br>Retrospective survey.<br>Only Car sharing members in the investigation. | No matter which car sharing scheme, users lower vehicle ownership levels.<br>Roundtrip station-based subscribers are almost 15 times more likely to shed a vehicle than FFCS unique members. |

# Chapter 3: EXPERIMENTAL SETTING AND DATA SET

This chapter contains three sections, starting with a summary of the current situation of car sharing programs in Germany. The focus on Germany is due to the fact that the survey of which we exploit the dataset is administered in that country, the only one to the best of our knowledge that organizes panel surveys in the transport sector whose datasets are publicly available. The chapter continues with a section describing the data set used in the study. It is finalized with survey results, especially car sharing and vehicle ownership, which are the main concern of this thesis.

## 3.1 Car sharing in Germany

The German car sharing industry has been growing steadily. In the Corona year 2020, market growth remained curbed due to the temporarily sharp decline in mobility demand during the two lockdowns. **Figure 3-1** shows car sharing statistics for Germany based on the key figures that the Bundesverband CarSharing eV (bcs[1]) requests from all car sharing providers in Germany on the key date of January 1 of each year. Looking to the statistics, as of January 01, 2021, there were 228 car sharing providers in Germany and 243 providers until January 01, 2022. They make their cars publicly available for sharing in 855 and 935 cities in 2021 and 2022, respectively. As of January 1, 2021, there were 2,874,400 authorised drivers in Germany with German car sharing services, which increased to 3,393,000 in 2022. That is 18 percent more than in the previous year. The growth shows that users trust car sharing even in times of pandemics. There are currently 30,200 car sharing vehicles available to customers. The German car sharing fleet grew by 15.2 percent compared to the previous year (2021) (bcs, 2022).

[1] https://carsharing.de/

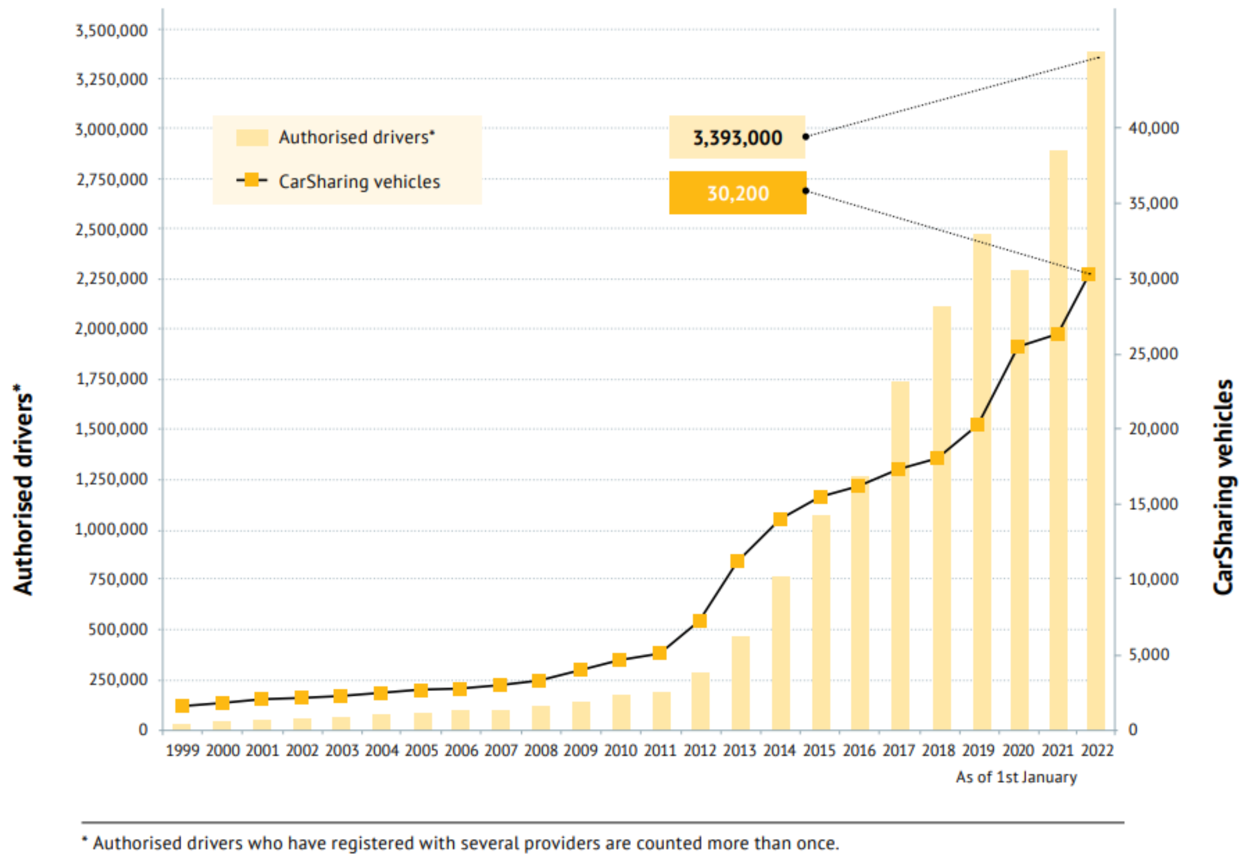


**Figure 3-1:** Market development of car sharing in Germany (bcs, 2022)

Station-based car sharing is the most widespread in terms of area. This type of car sharing is offered at all 855 Car sharing locations. The offer ranges from large commercial providers such as cambio[2], stadtmobil[3], teilAuto[4] or book-n-drive[5], who are active in several cities with large vehicle fleets, to associations that organize car sharing in rural areas voluntarily.

Free-floating car sharing is represented in 15 cities, mainly in large cities such as Berlin and Munich. The market is dominated by the four large providers, ShareNow[6], Sixt share[7], Miles[8] and WeShare[9], who offer Car sharing in a total of seven large cities and some of the suburbs of these cities. The number of combined systems that offer station-based car sharing and free-floating car sharing from a single source continues to increase. There are currently 20 places in Germany with such an offer. That is six more than last year. The largest providers of combined car sharing systems are stadtmobil, book-n-drive and teilAuto.

[2] https://www.cambio-carsharing.de/
[3] https://www.stadtmobil.de/
[4] https://www.teilauto.net/
[5] https://www.book-n-drive.de/
[6] https://www.share-now.com/de/en/
[7] https://www.sixt.com/share/locations/germany/#/
[8] https://miles-mobility.com/en
[9] https://www.we-share.io/

## 3.2 Introduction to the German Mobility Panel (MOP)

The German Mobility Panel (MOP) or Deutsche Mobilitätspanel in German is a longitudinal survey that has been conducted annually since 1994. From the beginning to 1998, it was based on the old federal states of Germany, but in 1999 the survey was outstretched to the entirety of the country. The study is funded by the German Federal Ministry of Transport and Digital Infrastructure (BMVI)[10], and the Institute for Transport Studies of the Karlsruhe Institute of Technology (KIT)[11] is in charge of the design and scientific supervision of the survey.

The goal of the MOP is to gain a general overview of travel in Germany. Thus, detecting the trends in travel behavior and explaining the mobility behavior are the solutions that can be done through the survey system. The survey is repeated every year, so the travel behavior in Germany has been observed continuously over the last 27 years. A large database and the results available by the MOP are used for research and policy purposes as well as to explore trends in mobility and behavioral changes, especially in longitudinal studies.

The MOP contains the socio-demographic background of the households. In addition to the population's everyday mobility, the study's subject is private cars' mileage and fuel consumption. The survey of daily mobility is usually carried out annually in autumn. The mileage and fuel consumption are then recorded in the spring. The exact survey period depends on the holidays and public holidays in the respective federal states. Moreover, The MOP has been expanded to study the effects of the COVID-19 crisis on mobility behavior, but it is not counted in this thesis.

### 3.2.1 Kinds of surveys and characteristics of the MOP panel

#### 3.2.1.1 Cross-sectional versus longitudinal panel data

Generally, there are four types of survey designs with specific characteristics, as **Table 3.1** shows the details (Tourangeau et al., 1997). The table distinguishes between two types of cross-sectional designs, one-time cross-sectional designs, and repeated cross-sectional designs, and two types of panel designs, longitudinal panel designs, and rotating or revolving panel designs.

Unlike cross-sectional surveys, longitudinal panel designs collect information on the same set of variables from the same sample members at two or more points in time. In a household travel survey, this means that questions about travel behavior and other variables are asked twice or more to the same sample of households. A wave or round of data collection refers to each distinct occasion during which sample members are surveyed. Respondents are asked to provide data twice for each wave in a two-wave panel survey. In a three-wave panel survey, panel members are asked

[10] https://www.bmvi.de/EN/Home/home.html
[11] https://www.kit.edu/

to provide data three times, and so on. Every wave typically collects both the same items of information and new items.

**Table 3.1**
Differences among the features of four types of survey design (Tourangeau et al., 1997)

| Approach | Design | Number of Distinct Samples | Number of Time Points | Number of Measurements Per Sample Members | Type of Variation Measured | | |
|---|---|---|---|---|---|---|---|
| | | | | | Variation Among Sample Members (Cross-sectional Variation) | Variation Within Sample Members Across Time (Longitudinal Variation) | Variation in the Population Across Time |
| Cross-sectional | One-time cross-sectional designs | One | One | One | Yes | No | No |
| | Repeated cross-sectional designs | Two or more (Same as the number of time points) | Two or more | One | Yes | No | Yes |
| Panel (Longitudinal) | Longitudinal panel designs | One | Two or more | Two or more (Same as the number of time points) | Yes | Yes | No |
| | Rotation panel designs | Two or more | Two or more | Two or more (generally less than the number of time points) | Yes | Yes | Yes |

Advantages of a longitudinal panel survey are the following points:

- It can provide data suitable for dynamic analysis. Being able to control the changes and patterns makes this approach so powerful.
- All the events are recorded, no matter whether they are predicted or not. This makes the correlation between the event and time clear.
- It limits many forms of measurement errors such as recall bias. In this type of study, information is recorded multiple times and alleviates recall bias.

Disadvantages of longitudinal panel survey are also mentioned below:

- There is a considerable risk of bias due to the drop-out of participants. It is crucial for the longitudinal survey to record the information multiple times, but it may happen that a number of participants are no longer available, and it makes the survey incomplete.

- Intra-subject correlation of response measurements should be taken into account by any analytical methods to avoid invalid results.
- The causality of changes should be checked by paying attention to the time and feedback between outcomes and the exposure.

Overall, cross-sectional is an approach in which data is collected at a single point in time, while in a longitudinal study, participants' responses, any treatment or exposure are collected at more than two follow-up times (Hedeker, 2006). Although performing a panel survey requires a great deal of effort, it is worthy because of the significant advantages provided for the researchers.

#### 3.2.1.2 Unbalanced panel survey and characteristics

Balanced panel data is when there is a constant number of observations all over the different waves, whereas it is called unbalanced when the observed ones are different from time to time (Baltagi and Song, 2006). Incomplete panel surveys are normal in the majority of the studies because of all the improvements and changes in the path in the middle of the way, unexpected reasons, changes in goals, simply differences in the sample population, etc. In the MOP, these unbalances also made some limitations in the analysis and evaluations.

#### 3.2.1.3 Rotating panel survey and characteristics

Rotating or revolving type of survey is a combination of repeated cross-sectional and panel designs (Tourangeau et al., 1997). It starts with collecting panel data for a period of time, then portions of the sample, for many different reasons, are dropped from the survey and the replacement process begins. Replacement is with new and comparable samples at the newest period. The reasons can be because of the unwillingness of the interviewees or a need when attrition is expected to be high. This procedure can be continued until the time that all the samples are replaced.

There are various advantages and disadvantages to a rotating panel survey, the most significant strength is opening the door to performing a short-time analysis of changes for every single unit and a long-time analysis of changes for the population. In the panel data, changes in the person or household level can be analyzed, and in the cross-sectional designs, there is information on how travel behavior changes over a period of time and at different levels of the population or other aggregates. Thus, the rotating panel is a combination of both types.

The method of sampling in the MOP data set is also rotating, meaning that participants of the survey are asked to fill the questionnaire for up to three consecutive years. Although, some households inevitably leave the survey after either the first or second wave. Therefore, there is always a plan to replace dropped households for the subsequent wave. A new cohort of first-year reporters replaces a portion of the sample that retires each year.

### 3.2.2 Reference universe and sample

All the German-speaking households living in Germany can be part of the project. The sample of households is collected based on households generally willing to provide information. These are determined by a computer-assisted telephone interview (CATI), a telephone surveying technique in which the interviewer follows a script provided by a software application. The survey is voluntary, and not all household members need to participate in order for the household to be considered a valid participant.

In the first interview, the project is explained to the households. In the further step, those households who showed interest in the first interview receive a letter, which again provides information about the project's goals and explains the survey modules and tasks that need to be done. After that, households have time to fill out the forms and questionnaires. To increase the coverage, reminders are sent to those who had not filled out the forms. It is remarkable that since 2013, respondents have been allowed to fill out the household questionnaire and the travel diary online as an alternative to the paper version. It is also noteworthy that the questionnaires are only available in German.

### 3.2.3 Data set description

Data were in two types, some of which were freely accessible on the MOP website[12] while other data should have been purchased. The freely downloadable documents were provided in different categories, including annual scientific reports (Wissenschaft-liche Berichte), time series of mobility parameters (Zeitreihen), reports of the survey institute (Berichte des Erhebungs- -instituts), survey documents (Erhebungsunterlagen), and code plan and manual (Codeplan und Handbuch).

Mobility Panel (MOP) survey are introduced in the reports. They present the methodology of the evaluation and the first evaluations of the data. Scientific annual reports contain Pdf files of reports for each year separately, the first results of the additional Corona survey 2020 and an overview of special thematic evaluations in the MOP reports. The time series contains xlsx files for each year separately, with tables in different sheets reporting a summary of the last ten years. The reports of data collection were in the “Reports of the survey institute” category in Pdf files for each wave separately. The survey documents were a household and personal questionnaire, a road diary, a questionnaire on car mileage and fuel consumption, and a questionnaire on car mileage and charging behavior. The code plan in two languages (German and English) was included in the last category called code plan and manual, also a Pdf file named “Guide to getting started with the MOP data structure”.

[12] https://mobilitaetspanel.ifv.kit.edu/Downloads.php

The main data purchased was The Mobility data (Mobilitätsdaten). The processed microdata of everyday mobility (up to wave 2020/2021), mileage, and consumption survey (up to wave 2020/2021) were stored separately for each year. It is noteworthy that these data were in three formats CSV, SAS, and SPSS. There was a folder for each year containing seven files until the year 2019/2020, which increased to eight files in the last wave. All these eight files are detailed in **Table 3.2**.

**Table 3.2**
Different data sets of the MOP

| Data sets | Description | Available from survey wave |
|---|---|---|
| HH | Data description of the household data file | 1994/1995 |
| P | Data description of the person data file | 1994/1995 |
| POT | Data description of the person-without trip-diary data file. These persons did not fill out the trip diary or the trip diary could not be used for further analysis. | 1996/1997 |
| KIND | Data description for the child data file. Children under 10 years are not asked to fill out the trip diary. Their personal data recorded by the household questionnaire is kept in this file. | 1994/1995 |
| PT | Data description of the person-day data file. This file contains only aggregated trip data by day. | 1999/2000 |
| W | Data description of the trip data file | 1994/1995 |
| TANK | Data description of the vehicle mileage and fuel consumption data file | 2001/2002 |
| AKKU | Data description of the vehicle mileage loading file | 2019/2020 |

**Note:** A survey wave of the MOP consists of the survey on everyday mobility in the autumn of a particular year, e.g., 2014, and the survey on car mileage and fuel consumption in the following spring, e.g., 2015.

There is a code book for each of data set listed in **Table 3.2**, in which the following information are explained. For each variable included in the data set, there might be up to seven related information. It begins with variable name of how it is shown in the data set. The second one is type of variables which gives information about the data type, and it could be one of the following options:

- Determined by the field work company
- Queried in the questionnaire
- Calculated on the basis of other questions / variables
- Supplemented from external sources

The next information provided is the exact question asked from respondents in the questionnaire. There is also a history question part in which all changes of the question (and the type of variable) are shown. Furthermore, the period where the questions was part of the questionnaire is shown. Next, there are two terms which “Since” defines the year of the survey wave where the variable was used for the first time. “Until” defines the year where the variable was changed/deleted. For all data sets the year where the everyday mobility in the survey wave took place is standard. The two last pieces of information are named “Answercode” and “Answer History” in which changes in answer code’s forms can be seen. For example, in one questionnaire the possible answers were “Checked” and “Not checked”, but in the next wave it changed to “Yes”, “No” and “Not respond”.

All the above-mentioned information were provided for each of data set file listed in **Table 3.2**, and for every single of their variables. As can be seen in **Table 3.3**, there are on average more than fifty variables included in each data set files. Although, only the first two data set were used in this thesis which are household and person data files.

**Table 3.3**
Number of variables listed in each data set files up to 2020/2021

| Data set | Number of variables |
|---|---|
| HH | 82 |
| P | 75 |
| POT | 33 |
| KIND | 16 |
| PT | 78 |
| W | 24 |
| TANK | 60 |
| AKKU | 47 |

**Note:** The number of variables in each data set might be different from one wave to another.

Among the many variables presented in the different data set files, some were selected key variables and are detailed in **Table 3.4**. It is noted that the reason for this selection is explained in **Section 4.4.3.1**. The variables under household and person levels are listed, with their specific names, in the MOP dataset. The meaning of each, as well as the classifications, are also described in detail. Notably, each of these variables is either numerical or categorical, which will be discussed more in **Section 5.1.2**.

**Table 3.4**
Key variables used in the present work

| Level | Variable name | Description and classifications | Type of data |
|---|---|---|---|
| Household | | | |
| | ID | Identification number of household | Numerical |
| | RAUMTYP | Type of region according to BIK, combined<br>- More than 100,000 inhabitants, home located in core region<br>- More than 100,000 inhabitants, home located in suburban area<br>- Between 20,000 and 100,000 inhabitants<br>- Between 5,000 and 20,000 inhabitants<br>- Less than 5,000 inhabitants | Categorical |
| | HHGRO | How many people permanently living in the household, you inclusive? | Numerical |
| | P0_10 | Number of children under the age of 10 | Numerical |
| | EINKO | How high is the net household income per month?<br>- Less than 500 €<br>- 500 up to 999 €<br>- 1,000 up to 1,499 €<br>- 1,500 up to 1,999 €<br>- 2,000 up to 2,499 €<br>- 2,500 up to 2,999 €<br>- 3,000 up to 3499 €<br>- 3,500 up to 3,999 €<br>- 4,000 up to 4,999 €<br>- 5,000 € and more | Categorical |
| | PKWHH | How many cars are permanently available to your household (including privately used company and company cars, without car sharing)? | Numerical |
| Person | | | |
| | ID | Identification number of household | Numerical |
| | PERSNR | Identification number of a single person within the household | Numerical |
| | SEX | Gender<br>- Male<br>- Female | Categorical |
| | ALTER | Age class<br>- Between 10 und 17 years old<br>- Between 18 und 25 years old<br>- Between 26 und 35 years old<br>- Between 36 und 50 years old<br>- Between 51 und 60 years old<br>- Between 61 und 70 years old<br>- Over 70 years old | Categorical |

| Level | Variable name | Description and classifications | Type of data |
|---|---|---|---|
| Person | | | |
| | SCHULAB | What is the Highest level of education?<br>- General certificate of secondary education<br>- University-entrance diploma<br>- University of applied science diploma, university diploma<br>- No graduation (yet)<br>- Secondary school | Categorical |
| | BERUF | Employment status<br>- Not employed: child, not in kindergarten<br>- Employed: full time<br>- Employed: half time<br>- Employed: temporarily unemployed<br>- Education: in school, at university, in further education<br>- Education: in vocational education<br>- Not employed: homemaker<br>- Not employed: retired<br>- Not employed: child, in kindergarten | Categorical |
| | FSPKW | Who has a car driving license?<br>- Checked<br>- Not checked | Categorical |
| | ZEITOPNV | Who has a season ticket for public transport (7-day, monthly, annual ticket)<br>- Checked<br>- Not checked | Categorical |
| | BAHNCARD | Who has a valid "Deutsche Bahn" railcard?<br>- Checked<br>- Not checked | Categorical |
| | PKWCS | Are you a member in a car sharing organization?<br>- No<br>- Yes | Categorical |
| | GEWHHPWO | Extrapolation factor at the person level | - |

**Note:** Classifications of some variables in the MOP were occasionally changed from one wave to another.

### 3.2.4 Sample size

Sample size refers to the number of respondents who complete the survey in each year. In **Figure 3-2**, the sample size of MOP in two levels of person and household is shown from 2005 to 2020. It is clear that the number of interviewees has constantly been increasing in MOP. More specifically, it experienced steady growth from 2012 to 2020, with 1173 households and 1913 individuals in 2012. It then recorded eighty percent growth, reaching 3461 individuals in 2020.

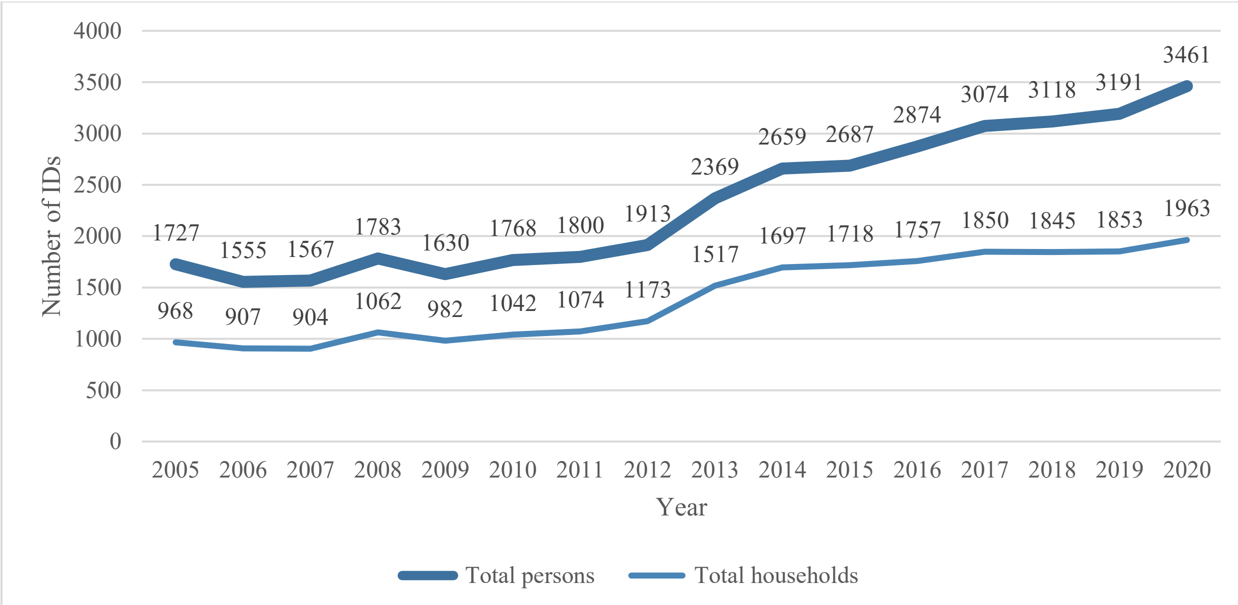


**Figure 3-2:** Sample size of each annual wave at both person and household level

## 3.3 Relevant MOP descriptive statistics

### 3.3.1 Car sharing in the MOP

In the survey, interviewees were asked if they are currently member of any car sharing company or not. This information was recorded in the person-level file (P file, data description of the person data file).

The number of people who reported being a member of any car sharing company was significantly low during all the years in the MOP compared to the sample size. Therefore, such data have not been traditionally considered in car sharing patterns of use analyses due to a very low number of observations. However, it can be noted that in more recent years, the larger diffusion of car sharing is also mirrored in this survey. Therefore, we will base our analyses on the MOP data set, trying to exploit the benefits of panel data to answer the research question described in the introduction. The sample size, considering household and person-level IDs, were shown in the above **Figure 3-2**.

However, knowing car sharing members in each year, **Figure 3-3** (Dual axis chart) and **Table 3.5** show absolute number of carsharer and also households with at least one car sharing member. The maximum number of IDs recorded in 2020 was 3461 individuals in total, when only 83 drivers were using shared car services. The second highest car sharing members was recorded in the year 2019 with 63 members from 3191 individuals.

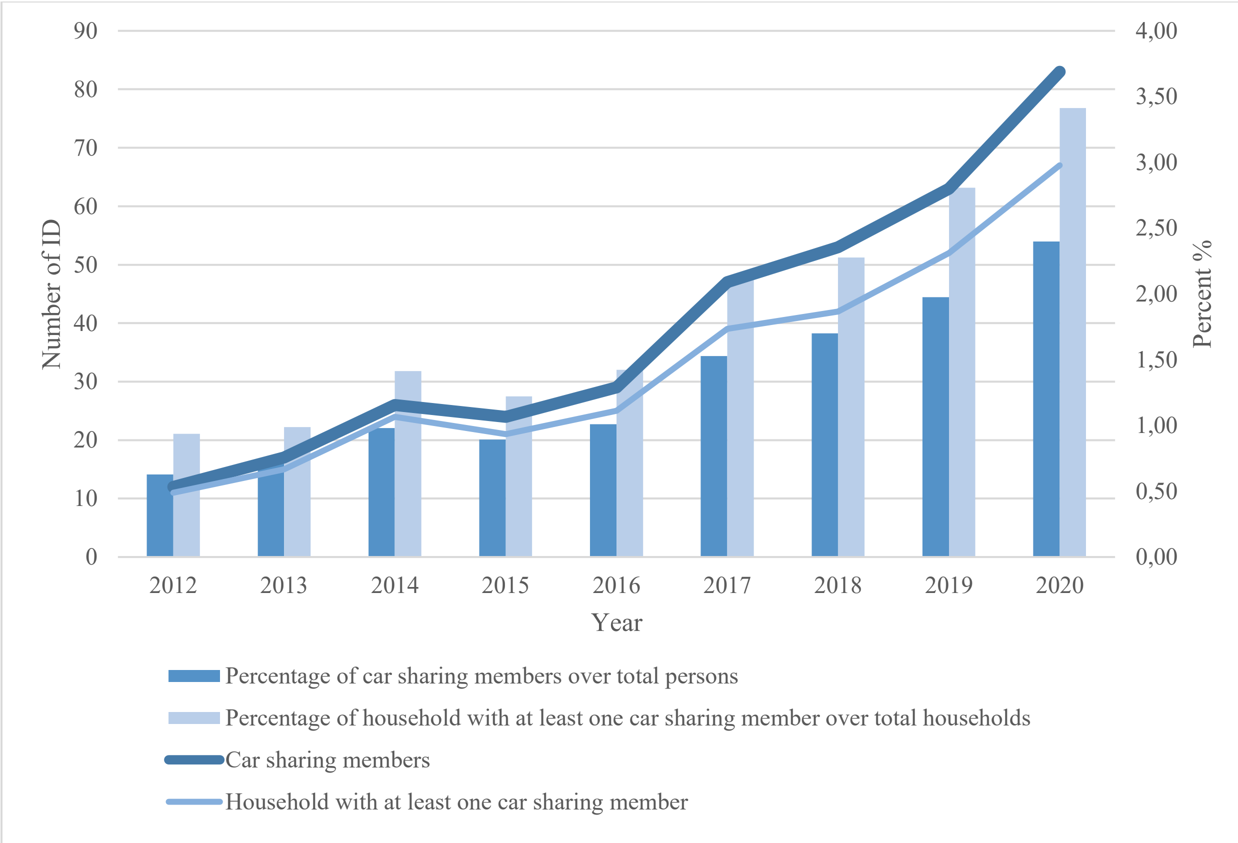


**Figure 3-3:** Car sharing in the MOP

**Table 3.5**
Car sharing in the MOP (Quantitative information of **Figure 3-3**)

| Year | CS members | Percentage of CS members over total persons % | HH with at least one CS member | Percentage of HH with at least one CS member over total HH % |
|---|---|---|---|---|
| 2012 | 12 | 0,63 | 11 | 0,94 |
| 2013 | 17 | 0,72 | 15 | 0,99 |
| 2014 | 26 | 0,98 | 24 | 1,41 |
| 2015 | 24 | 0,89 | 21 | 1,22 |
| 2016 | 29 | 1,01 | 25 | 1,42 |
| 2017 | 47 | 1,53 | 39 | 2,11 |
| 2018 | 53 | 1,70 | 42 | 2,28 |
| 2019 | 63 | 1,97 | 52 | 2,81 |
| 2020 | 83 | 2,40 | 67 | 3,41 |

**Note**: CS is the abbreviation of car sharing.

### 3.3.2 Car ownership in the MOP

Car ownership has been recorded in MOP at the household level and so in the HH file (data description of the household data file). Therefore, the number of cars is actually the number of cars in each household. As can be seen in **Figure 3-4**, the percentage of HH car holding status were almost similar during the survey period (2012-2020). It is noted that around 50 percent of the household in all the years had only one vehicle, and then two-car owners were almost 25 percent of the households. Notably, there was less than 15 percent of households owning no vehicle in all the waves.

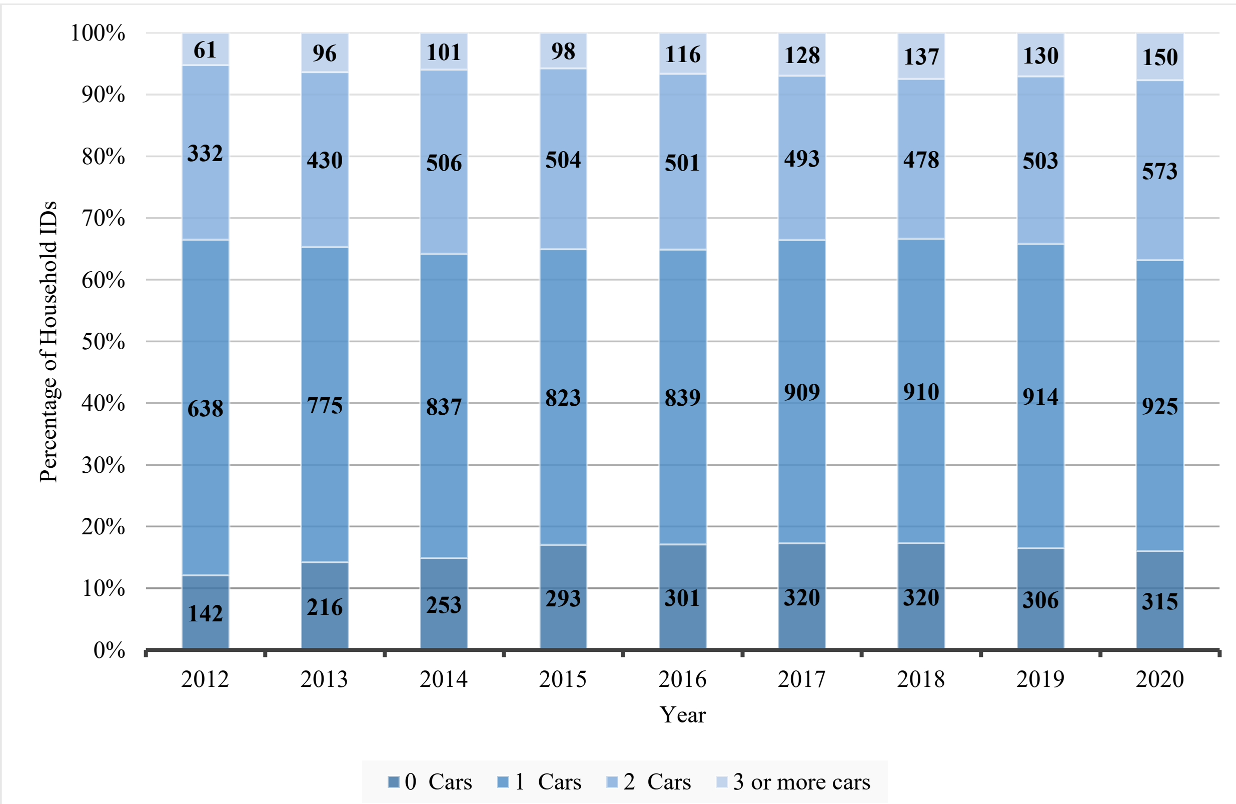


**Figure 3-4:** Car ownership levels in the MOP

On the other hand, the level of car ownership in households with at least one car sharing member is shown in **Figure 3-5**, where on average, 60 percent of households were carless throughout all the waves. The second highest group was households owning one car, with around 25 percent. It is noteworthy that the minority of the households owned two or more vehicles. For example, there was no household holding more than one car among those having at least one car sharing member.

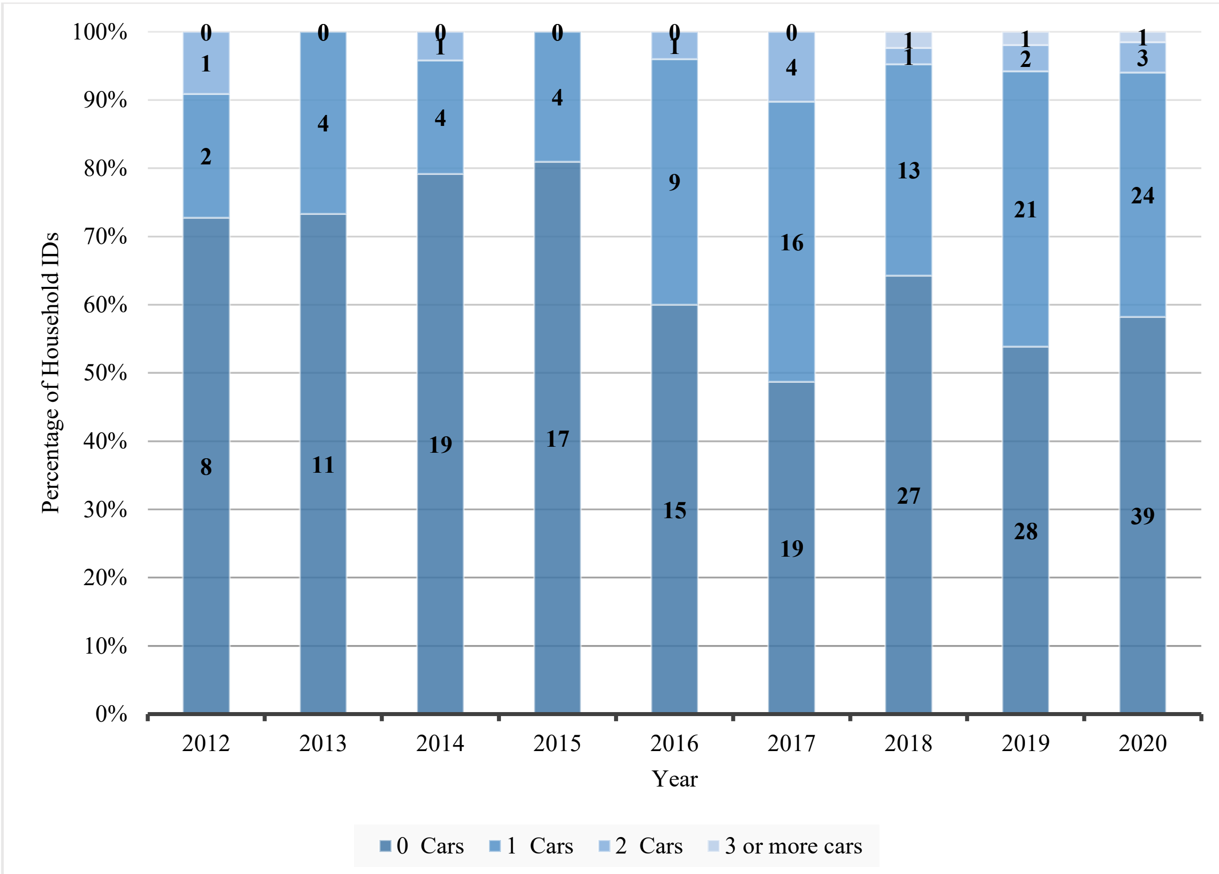


**Figure 3-5:** Car ownership levels in the households with at least one car sharing member

The level of car ownership was shown in two figures, one related to all the households and another when at least one person subscribed to a car sharing program. Comparing **Figure 3-4** and **Figure 3-5**, a significant difference can be seen in the case of households with the non-owning vehicle, where more than half of the households with at least one car sharing member had no car, while less than 15 percent of whole households were carless. This shows that owning no car can possibly increase the tendency to subscribe to a car sharing program. Another difference between these two figures is households owning more than one car. The higher the car ownership level, the lower tendency to be a car sharing member. On average, less than 5 percent of the households with at least one car sharing hold more than one vehicle, while more than 30 percent among all the households in the survey.

The two above bar charts are based on panel data, therefore observations between consecutive years are partially referring to the same household. In order to exploit the advantages of such kinds of data, it is needed to go beyond annual descriptive statistics. Therefore, a dynamic analysis of car ownership changes versus (un)subscription to car sharing is proposed in the following.

# Chapter 4: METHODOLOGY AND PREPARATION OF DATA

Chapter four explains the research methods and design used to conduct this study. The first section details the concept of causal effect and biases faced in car sharing. Then, the control group in scientific investigations and matching method are explained. The last section of this chapter shows how data were cleared and prepared for further matching analyses.

## 4.1 Validation issue

The validation of a model is a process of confirming that its purpose is actually achieved. In most situations, this will involve confirmation that the model is predictive under the conditions of its intended use. Validation checks a model's accuracy and performance.

### 4.1.1 Causality effect

In research, causality is an important and widely used term. The concept of causal effect was officially introduced by Donald Rubin in 1976 (Rubin, 1976) and further explained by Rubin and Paul Rosenbaum in 1983 (Rosenbaum and Rubin, 1983) as well as Paul Holland in 1986 (Holland, 1986). Causal effect is when something happens or is happening as a result of something that occurred or that is happening. In other words, it is a phenomenon that makes a change in a second event or action. Usually in research, there are two types of variables, one is dependent and another one is independent. By referring to a causal relationship or a cause-and-effect relationship between two variables, it means a change in the independent variable causes a change in the dependent variable.

Cause-and-effect relationships have three main components which are temporal sequence (Prior to the effect, there must be a cause), non-spurious association (The covariation between the causal relationship must be true and not due to an intervening or unaccounted variable that influences the relationship) and concomitant variation (The variation between two variables must be systematic and must therefore occur or vary together).

All in all, it is very difficult to prove causality. Some researchers believe that causality cannot be demonstrated with finality, and that the best they can do is generate increasingly compelling evidence that is consistent with causality.

### 4.1.2 Biases

Bias is the tendency for collected data to differ from what is expected in a systematic way. Biased data can often favor a specific group of those studied. Bias jeopardizes the accuracy of the data collected. Studies can be caried out and evaluated better if the different types of bias can be recognized.

#### 4.1.2.1 Self-selection bias

There are many different types of selection bias, but self-selection bias is a term used most often in statistics when referring to data gathered by survey. Self-selection bias is a problem that frequently occurs when survey respondents are given complete freedom to choose whether or not to participate in a survey. There will be self-selection bias in the generated data to the extent that respondents' propensity for participating in the survey is connected with the substantive topic the researchers aim to examine.

One of the reasons data might be missed is that the survey is not accessible to a representative population to choose to take, especially in online surveys. Another big reason leading to missing data is that participants are only likely to opt into a survey if it is something they feel strongly about. People rarely take the time to fill out a survey if they do not feel passionate about the item the survey is measuring. That leads to bias in the data because it is not representative of a broad population but only a small section with strong feelings on the survey topic.

This bias in car sharing studies describes situations where sociodemographic characteristics of the survey respondents that cause them to select themselves in the group and create undesirable or abnormal conditions. Members and non-members differ in various observed and unobserved ways, and it raises the potential for self-selection bias in comparing travel behavior between the two groups given the observational nature of the MOP data. A person who subscribes to a car sharing company is likely to have significant differences in socio-demographic, including car ownership levels, compared to a person who has never been a member. Indeed, compared to non-members, members are less likely to own a car even before membership, are younger and more educated, and live in smaller households in urban centers (Loose, 2010; Martin et al., 2010; Sioui et al., 2013).

Car sharing effects on car ownership are usually evaluated through cross-sectional studies comparing members and non-members. Nevertheless, since self-selection bias might be present, it can be difficult to assess a causal link between membership in car sharing and ownership of a vehicle. This study considers the effect of self-selection by using propensity score-based matching to avoid any potential prejudgment towards the impacts of enrollment of car sharing on car ownership.

#### 4.1.2.2 Recall bias

The recall bias occurs when individuals differently self-report information about past exposures or outcomes. A key consideration is whether the measurement errors are likely to differ (in terms of frequency, magnitude or direction) between cases (treated) and controls. A study's validity is often threatened more by differential errors than by non-differential errors. This is a primary problem for retrospective studies. Self-reporting may be the most common data collection method in car sharing studies e.g., Martin and Shaheen (2011) and Martin et al. (2010). A common finding of recall studies is that it is both the type of data sought and the methodology used that determine the quality of information (Kopec and Esdaile, 1990).

According to Raphael (1987), it is noted that recall bias is not the same as memory failure itself. There will be no recall bias if memory failure regarding prior events is equal in the case and control groups. The failure of memory itself leads to measurement errors, which reduce statistical power.

One of the first comprehensive study was conducted in Switzerland on the impact of car sharing on travel behavior (Muheim and Reinhardt, 1999). In a survey, participants reported their travel behavior both currently and retrospectively before they joined a car sharing membership. It must be assumed that recall bias results from a retrospective survey approach like this (Kopec and Esdaile, 1990; Mokhtarian and Cao, 2008). In order to overcome recollection bias, Cervero and Tsai (2004) and Cervero et al. (2007) delivered their survey to a panel in many waves in a longitudinal environment, which was the first to address these issues. Furthermore, the use of a control group was intended to enable separation of the true impacts of car sharing participation from unrelated effects. In this thesis also the data used was longitudinal panel data with nine waves and propensity score-based matching method was used to construct the control group.

## 4.2 Control group concept

In scientific studies, a control group is used to isolate an independent variable's effect to establish cause-and-effect relationships. The independent variable is changed in the treatment group but kept constant in the control group, then the two groups' results are compared.

Research with control groups helps ensure its internal validity. In your treatment group, you may see changes in your dependent variable over time. However, if there is no control group, it can be difficult to determine whether the change has arisen from the treatment. There is a possibility that other variables contributed to the change. On the other hand, by using a control group that is identical to the treatment group in every way, you can be certain that the treatment, which is the only difference between the two groups, is the cause of the change.

It is possible that your results reflect the interference of confounding variables rather than the independent variables if the control group differs from treatment group in ways that you haven't accounted for in your analysis. When researchers investigate a potential cause-and-effect relationship, a confounding variable is an unmeasured third variable that influences both the supposed cause and the supposed effect. You must take confounding variables into account to guarantee the internal validity of your research. If you don't, your findings could not accurately reflect the link between the variables you're interested in. The impact of confounding variables can be reduced in several methods, one of them is matching which will be discussed in **Section 4.3**.

In this study, the treated group contains all the members who have been car sharing members at least one time in this period and the control group is made with never car sharing members. This makes it possible to compare car ownership level of these two groups and define the effect of the changed variable i.e., car sharing membership.

## 4.3 Matching method

The basic idea of matching method is to compare units that have the same values of the covariates, but different values of the treatment. To do so, we first construct the treated unit and then find the non-treated unit that has very similar covariates values. That pair is called a match. Matching sample, which is a statistical method, has been used in many disciplines such as political and legal studies, epidemiology and medical research, and economics. Similarly, in car sharing studies such as two investigations conducted by Mishra (Mishra et al., 2015, 2019) about the effect of car sharing on vehicle holding and travel behavior.

The participants in matched samples (also called matched pairs, paired samples, or dependent samples) are paired so that they share all characteristics except the one being studied. The term "participant" refers to a person, object, or thing that is a part of the sample. The assignment of one person to a treatment group and another to a control group is a frequent application of matched pairs.

On the other hand, the opposite of a matched sample is an independent sample, which deals with unrelated groups. Whilst matched pairs are deliberately chosen, independent samples are typically chosen at random.

In order to select the control group from the available observations, a matched sampling procedure was adopted. Researchers are often faced with studies with a small number of treated and a large number of controls like this study. Matching is a technique to choose participants of the control group, meaning that the particular covariates selected by the researcher from the treated group are matched to the control group. Essentially, matching aims to balance the distribution of observed confounding variables between the control and treated groups in such a way that they can be attributed to the treatment under study for differences in outcome between them.

There are many different methods to pick the pairs, but all have the same basic idea, finding units with similar values of their covariates. One of the most popular methods for matching is called propensity score matching.

### 4.3.1 Propensity Score Method

It is often difficult to match covariates, even with numerous potential participants. Especially when there are many variables to be matched, in this case, propensity score matching is the one solution which also used in this thesis. Using propensity score, one can statistically balance different observed socio-demographic characteristics between the treated (car sharing members) and the control group (never car sharing members). The advantage of propensity score matching is that only by a single scalar variable can it control all the selected covariates simultaneously. In other words, a propensity score is a single number that summarizes all that unit's covariates. Therefore, by first computing this number for all the units, it is then possible to just compare units along that single number. The closer the numbers, the better matching.

The propensity score is defined as the conditional probability of being treated in the presence of covariates, and these covariates can be balanced in the two groups. Thus the bias can be reduced. In theory, the propensity score is a measure of how likely it is that a person would have been treated based only on their covariate scores. When we find two subjects with the same propensity score, one in the treated group and one in the control group, we can suppose that these two subjects were randomly assigned to each group in the sense that either group was equally likely to receive either treatment or control. Even though the results of using propensity scores only depend on observed covariates, if one is able to measure many of the covariates that are believed to be related to treatment assignment, one can be fairly confident that an approximately unbiased estimate can be obtained (D'Agostino Jr, 1998). It is demonstrated in large and small sample theory that adjustment for the scalar propensity score is adequate for removing bias caused by all observed covariates (Rosenbaum and Rubin, 1983).

### 4.3.2 R software and its MatchIT package

There are different software able to perform matching (Parsons, 2000; Abadie et al., 2004; Becker and Ichino, 2002; Leuven and Sianesi, 2003; Hansen, 2005). In this thesis, propensity score matching to construct the control group was undertaken by using the MatchIT package in R software (Ho et al., 2013) which is a free statistical programming language. MatchIt is available from the comprehensive R archive network at http://CRAN.R-project.org/package=MatchIt.

MatchIT package defines the rules for the matching procedure, such as the methods, limitations, identification of dependent and independent variables, and so on. It is remarkable that the goal of using MatchIT is to reduce the bias, but sometimes it could cause discarding too many observations from the input data, which can be biased and inefficient. For example, if a rule is set through the MatchIT, which makes the observations drop, it can easily neglect many treated observations. This is the worst case because the number of treated individuals in the studies is usually limited compared to the control group.

There are typically four following main methods to perform the matching with this package in R and each has advantages and disadvantages.

The first method is "Exact" matching. This is the simplest way to do the matching, considering that this method checks all the control group units for every treated unit to be identically matched. This means that all the variables must exactly be the same in two groups to be defined as matched. Although this can be described as a strength of this method, but at the same time this can easily discard too many observations. The problem with exact matching is that in general, few if any units will remain after matching, so the estimated effect will only generalize to a very limited population and can lack precision. Exact matching is particularly ineffective with continuous covariates, for which it might be that no two units have the same value, and with many covariates, for which it might be the case that no two units have the same combination of all covariates. Consequently, this method was not suitable for our study.

The second matching method is called "Nearest-neighbor" matching. This method uses the propensity score calculated from the logistic regression for each individual in the treated and control groups and searches for the best matches. In other words, involves running through the list of treated units and selecting the closest eligible control unit to be paired with each treated unit. The best matches are based on the criteria defined in the formula, for example, how close should be their propensity score or how many control group members should be found for each treated group. It is noted that when using a matching ratio greater than one (i.e., when more than 1 control units are requested to be matched to each treated unit), matching occurs in a cycle, where each treated unit is first paired with one control unit, and then each treated unit is paired with a second control unit, etc.

Another method is called "Optimal pair" matching. This method like the nearest neighbor method is based on finding the closest match (propensity score) for each treated unit. Although in the nearest neighbor method there is no control on minimizing a global distance, in the case of optimal matching matches are found with the smallest possible average distance through all of the paired matches.

The last method is "Optimal full matching". This method refers to a type of subclassification that forms subclasses in an optimal way (Rosenbaum, 2002; Hansen, 2004). More specifically, the result is the sets of matches in which there are one treated unit and either one or more control units. It could be also vice versa based on the preference. The results in each subclass are optimized in terms of minimizing the weighted average of the distance between each of two groups (treated and control) of units.

The main disadvantage of optimal full matching method was the difference between the number of control units found per each treated unit. It was necessary for this thesis to construct the control groups with the same ratio in all the waves.

Taking everything into the account, nearest-neighbor method with the ratio of five was selected for this study. Nearest neighbor matching is the most common form of matching used (Thoemmes and Kim, 2011; Zakrison et al., 2018) and has been extensively studied through simulations. Optimal pair matching and nearest neighbor matching often yield the same or very similar matched samples; indeed, some research has indicated that optimal pair matching is not much better than nearest neighbor matching at yielding balanced matched samples (Austin, 2013).

## 4.4 Data clearance and preparation

As shown in **Table 3.4**, the "ID" column in the data set actually corresponds to household ID, meaning that all the members in each household have the same ID, while it was needed to recognize each individual separately. To solve this problem, a univocal person ID was derived by merging household ID and PERSNR[13] column therefore deriving a new identifier called ID_der. The following **Table 4.1** is an example of this process to derive a unique ID for each person in the sample.

**Table 4.1**
Derivation of a unique ID

| ID | PERSNR | ID_der |
|---|---|---|
| 330010 | 4 | 330010_4 |

**Note:** All the numbers in this table are only as an example of how ID_der was derived.

After driving a unique ID for each person, all the ID_der with empty PKWCS[14] column (Missing answers) were discarded to find only valid observations.

**Table 4.2** shows that between 8 to 15 percent of individuals did not identify whether they used car sharing programs or not, and they are therefore discarded from the rest of analyses.

**Table 4.2**
Number of valid observations and non-car sharing members

| | Year | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 |
| Total observations | 1913 | 2369 | 2655 | 2687 | 2874 | 3074 | 3118 | 3191 | 3461 |
| Missing answers | 191 | 377 | 367 | 307 | 235 | 315 | 350 | 375 | 392 |
| Valid observations | 1722 | 1992 | 2288 | 2380 | 2639 | 2759 | 2768 | 2816 | 3069 |
| Non-members | 1710 | 1975 | 2262 | 2356 | 2610 | 2712 | 2715 | 2753 | 2986 |

**Note:** Total observations are in person level. Missing answers are the excluded observation with empty PKWCS cells. Non-members are those individuals with PKWCS cells equal to 0.

[13] Identification number of a single person within the household.
[14] Are you a member of a car sharing organization?

Notably, comparing **Figure 3-3** and **Table 4.2**, it is obvious that valid observations contain no-members and car sharing subscribers each year.

### 4.4.1 Identification of observations for the Treated group (Car sharing members)

The treated group was built using the Excel spreadsheet. As was mentioned in **Section 3.2** the MOP data set is in two levels of person and household in all the waves. It is noted that many of the sociodemographic characteristics interested in this study are at the person level. Therefore, transferring all the variables to person level has been considered. First, these two levels were merged using the "VLOOKUP" function in Excel to combine all the information about different socio-economic characteristics for each person of each household and in each year separately. Then all the characteristics moved to person_level. In the end, just by simply filtering the "PKWCS" column, which is "1" for car sharing members and "0" for non-members, all the carsharing members in each year were found. At this point, there were car sharing members in different years separately. It must be pointed out that we call "ID" instead of "ID_der" from now on in this study for the sake of simplicity.

Car sharing members range from 0.60 to 2.40% of all observations between 2012 and 2020, as shown in **Table 3.5**. Also, only about 1.4% of car sharing members are among all the observations. Since the study performed the longitudinal survey, some members were present for more than one year, resulting in a limited number of subscribers participating in the survey. Consequently, it was expected to construct the treated group with relatively few numbers of IDs.

Since this thesis was designed to deal with longitudinal analysis, car sharing members in all the years and their car ownership changes over the years were needed. Therefore, it was needed to check every member's situation in all the years to find when exactly they subscribed or unsubscribed and whether they sold or bought any of their own cars in which year.

As a first step, car sharing members in different years were combined in one column removing duplication. This was done by checking "Duplicate Values" command in Excel for two consecutive years, for example, 2012 and 2013. Then all the remaining IDs were listed under the 2012 column. The process was iterated for all remaining years up to 2020. In the end, a list of unique car sharing members in one column was obtained. Having merged all the years without duplication, considering one person might be interviewed in two or three years, 233 unique car sharing members were spanning these nine years (2012-2020). This list of car sharing members are listed in **Appendix A.**

Using the "VLOOKUP" function in Excel by referring to the original data, it was then possible to obtain car ownership (PKWHH) and car sharing membership status (PKWCS) information of each of these 233 car sharing members in the different years. **Appendix A** details the number of owned cars and the car sharing membership status over time for the treated group.

However, not all the above mentioned 233 observations can be considered in the treated group for longitudinal analysis. Only those observations satisfying all the following three conditions are useful.

- At least two years of information are needed for each ID.
- Unclear patterns of PKWHH and PKWCS (car ownership and car sharing membership) for all the IDs should be discarded, as detailed below.
- Only one randomly selected person in each household can be in the treated group, given the prevailing shared use of cars at household level.

Concerning the first point, it is required to have at least two years of information because changes over time in car ownership and car sharing situations are jointly analyzed in this study, which means only one information prevents any dynamic analysis.

Regarding the second point, some unclear patterns were observed since the aim is to determine members' behavior toward being subscribed to a car sharing company and whether it affects their car ownership. The aim is to recognize any increasing or decreasing changes in car ownership over time while there is clear information about individuals' membership situations. Unclear patterns that are present in the dataset are the following ones:

- Pattern "1-2-1" for car ownership: This pattern referred to an individual living in a household with one vehicle in the first recorded year, two in the second year, and again one in the third year. It is unclear whether this person increased or decreased car ownership throughout the observation period.

- Patterns "0-1-0" or "1-0-1" for car sharing membership: This pattern referred to an individual living in a household who was not a car sharing member in the first recorded year, but in the second year, a subscription was reported, and again this person unsubscribed in the last interview. This means it is not clear whether this person is a car sharing member or not because the subscription situation should be known to be able to do any analysis, while in this situation, many factors might have affected this membership.

The last point is about random selection of only one car sharer in each household. Participants are randomly assigned to treatment groups to balance other factors that may affect the outcome, such as age and gender. By canceling out the impacts of these variables, any differences between groups are due exclusively to the treatment imposed by the researcher, not to demographics or participant characteristics. As a result of random sampling, your results have higher external validity or generalizability, since they are more representative of the whole population. In this way, you can make stronger statistical inferences.

As can be seen in **Table 4.3**, having only one-year information was the main reason for discarding car sharing members before constructing treated group.

**Table 4.3**
The number and reasons of discarded IDs for construction of treated group

| Reason for discard | Number of discarded IDs |
|---|---|
| Only one-year information | 83 |
| "1-2-1" pattern in PKWHH | 1 |
| "0-1-0" or "1-0-1" pattern in PKWCS | 11 |
| Randomized selection of one car sharing member in each household | 23 |
| Total | 118 |

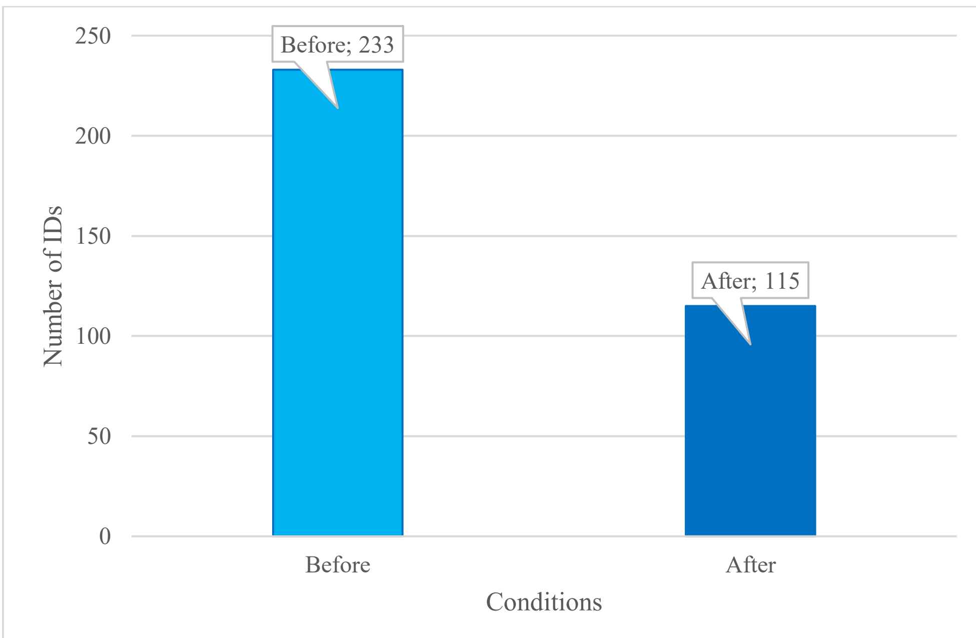


**Figure 4-1:** Number of car sharing members before and after discards for constructing the treated group

In the end, 118 observations were discarded, which limited the observations reducing from 233 to 115 as shown in **Figure 4-1**. After all the discards, a new table was created. It is worth mentioning that discarded patterns are shadowed in grey in **Appendix A**.

As it can be seen in **Table 4.4**, the number of IDs belonging to the treated groups almost increased in these nine years. The lowest number was recorded in 2012, with 5 IDs. However, there was a peak in 2019 when there were 41 IDs in the treated group. It is also noted that each ID pertained to more than one year because all the one-year information were discarded (**Table 4.3**). This means a car sharing member in one year's treated group was also present at least in another year, and not more than three years. Thus, the sum of the treated IDs was 209 instead of 115.

**Table 4.4**
Potential treated groups

| Year | Number of IDs in each potential treated group after all the discards |
|---|---|
| 2012 | 5 |
| 2013 | 12 |
| 2014 | 16 |
| 2015 | 17 |
| 2016 | 22 |
| 2017 | 31 |
| 2018 | 37 |
| 2019 | 41 |
| 2020 | 28 |
| Total | 209 |

### 4.4.2 Identification of the observations for the Control group (Never Car sharing members)

Individuals can only be included in the control group if they have never been a member of a car sharing program during all the years in the MOP survey. This was because treatment was actually being a car sharing subscriber, no matter in one year or three consecutive years.

Car sharing members, valid observations, and non-members in each wave were already known in **Table 4.2**. However, potential control group members were not simply non-members in each wave. There was a systematic error to only find the potential control group members by comparing each wave separately. Because there was a possibility that an individual was not a car sharing member in a specific year and so wrongly identified as a potential control group member. Nevertheless, this individual might have been a car sharer in another year.

Identification of the control group began with removing all 233 unique car sharing members and their corresponding IDs (see **Section 4.4.1**) from valid observations in all years, not just from the one when membership of each ID was reported. As can be seen in **Table 4.5**, the first potential control group members were calculated, while the difference between valid observation numbers and control groups were not equal to car sharing numbers in each year. For example, 83 car sharing subscribers were in 2020 (see **Table 3.5**), while the difference between 3069 valid observation and 2972 potential control group members was 97 IDs.

**Table 4.5**
Potential control groups_1

| | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | Total |
|---|---|---|---|---|---|---|---|---|---|---|
| Valid Observations | 1722 | 1992 | 2288 | 2380 | 2639 | 2759 | 2768 | 2816 | 3069 | 22433 |
| Potential control groups_1 | 1707 | 1969 | 2251 | 2341 | 2592 | 2698 | 2692 | 2733 | 2972 | 21955 |

**Note:** “Potential control groups_1” means those who were never been a car sharing member in all the years.

As a next step, using Excel spreadsheet, members of Potential control group_1 in different years were combined in one column removing duplication. Similar to treated group process, this was done by checking "Duplicate Values" command in Excel for two consecutive years, for example, 2012 and 2013. Then all the remaining IDs were listed under the 2012 column. The process was iterated for all remaining years up to 2020. In the end, a list of unique IDs in one column was obtained. Having merged all the years without duplication, considering one person might be interviewed in two or three years, 11812 unique IDs were spanning these nine years (2012-2020). Using the "VLOOKUP" function in Excel by referring to the original data, it was then possible to obtain car ownership status (PKWHH) of each of these 11812 potential control group members in the different years.

However, not all the above mentioned 11812 observations can be considered in the control group for longitudinal analysis. Only those observations satisfying all the following three conditions are useful. It is noted that these conditions are equal to the condition applied on potential treated group members. (Three conditions were explained in **Section 4.4.1**)

- At least two years of information are needed for each ID.
- Unclear patterns of PKWHH and PKWCS (car ownership and car sharing membership) for all the IDs should be discarded.
- Only one randomly selected person in each household can be in the control group.

These discards have been processed step by step. As seen in **Table 4.6**, 5049 out of 11812 IDs have been discarded because of only one year of data which causes the prevention of dynamic analysis. Considering the unclear patterns, all the possible patterns in car ownership, which may have caused confusion, have been checked. The total number of ID discards caused by these first two conditions were 5103 IDs.

**Table 4.6**

The number and first two reasons of discarded IDs for construction of control group

| Reason for discard | Number of discarded IDs |
|---|---|
| Only one-year information | 5049 |
| | |
| PKWHH patterns | |
| "1-2-1" | 10 |
| "0-1-0" | 1 |
| "2-3-2" | 10 |
| "3-4-3" | 0 |
| "4-5-4" | 0 |
| "5-6-5" | 0 |
| "1-0-1" | 4 |
| "2-1-2" | 16 |
| "3-2-3" | 13 |
| "4-3-4" | 0 |
| "5-4-5" | 0 |
| "6-5-6" | 0 |
| | |
| Total | 5103 |

**Note:** This table contains all possible PKWHH (Car ownership status) patterns conditions, even though some of them were not seen among the potential control group_1.

The last discard rule was about randomly selecting only one person in each household still in the pool after the two previous selections for households with at least two members, whereas one-member households clearly did not need this treatment. Finally, after all the discards, 4428 IDs remained, as shown in **Figure 4-2** , which means a reduction of around 40 percent in the number of potential control group IDs.

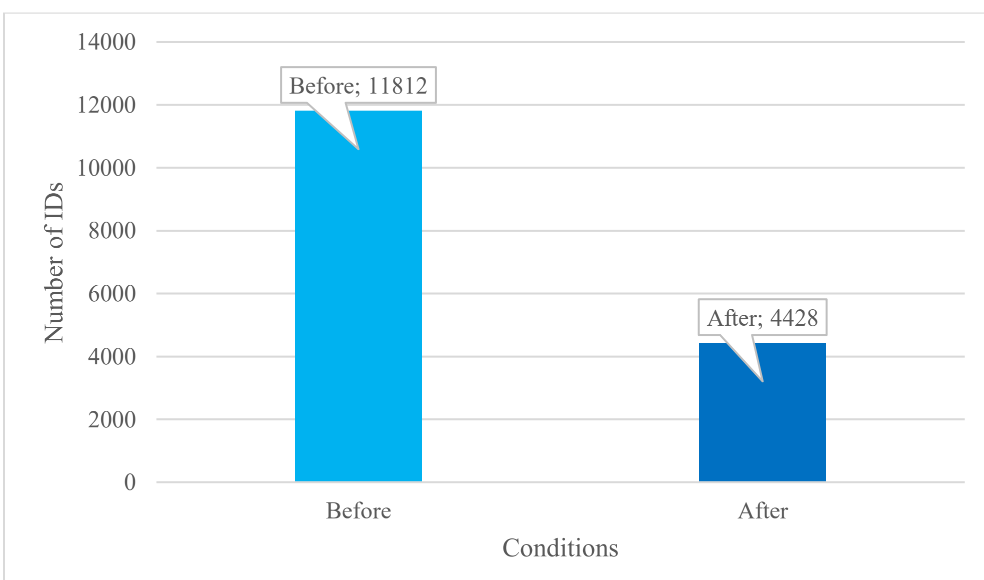


**Figure 4-2**: Number of control group IDs before and after discards for constructing the control groups

Exactly like treated group, here also each ID pertained to more than one year because all the one-year information were discarded (**Table 4.6**). This means an individual in one year's control group was also present at least in one more year. Thus, the sum of the control group IDs was 11035 instead of 4428, as can be seen in **Table 4.7**.

**Table 4.7**

Potential control groups_2

| Year | Number of IDs in each potential control groups after all the discards |
|---|---|
| 2012 | 581 |
| 2013 | 1057 |
| 2014 | 1251 |
| 2015 | 1312 |
| 2016 | 1403 |
| 2017 | 1490 |
| 2018 | 1497 |
| 2019 | 1479 |
| 2020 | 965 |
| Total | 11035 |

## 4.4.3 Preparing treated and control groups for the MatchIT

The potential treated and control groups were found so far. However, it was required to take into consideration also other points to finalize these two groups. These points are mainly related to the software used for the analysis, which will be discussed more in the following paragraphs.

### 4.4.3.1 Socio-demographic variables

In order to use propensity score matching, the first step is to select the variables to be used. It is ideal for propensity scores to be created from covariates associated with participants' self-selection into an intervention. Including or excluding key covariates affects the accuracy of a researcher's inferences about an intervention's effect (Brookhart et al., 2006; Steiner et al., 2010). Covariates should be carefully selected, as propensity score matches will only be made based on those included in the model.

Variables related to self-selection into the intervention and to the outcome of interest are key covariates (Stuart, 2010). For example, being car sharing member is the independent variable in this study, and so education and occupational level, holding driving license and car ownership were likely effective covariates. On the other hand, variables unrelated to self-selection or the outcome of interest are likely not effective covariates unless they serve as proxies for related covariates. (Harris and Horst, 2016). Therefore, using a large set of covariates is recommended, even if some of the covariates are not necessarily related to the result of interest; rather, they are only related to self-selection and other covariates (Stuart and Rubin, 2008).

Socio-demographics refers to a combination of social and demographic factors that define an individual in a group or population. Social and demographic characteristics can help explain group members' mobility behavior. There are several important sociodemographic factors that have been mentioned in the literature and that have been taken into consideration in this study, including gender, age, educational level, employment status, driving license, seasonal and discount card, residential area, household size, the presence of children in household, economic status, and vehicle ownership status. All these variables are shortly explained in **Table 4.8**.

**Table 4.8**
Key variables used in this study

| Covariates name | Level | Description | Type |
|---|---|---|---|
| RAUMTYP | Household | Region, inhabitants | Categorical |
| HHGRO | Household | Permanent people living | Numerical |
| P0_10 | Household | Children under 10 | Numerical |
| EINKO | Household | Net Monthly income | Categorical |
| PKWHH | Household | Car ownership | Numerical |
| SEX | Person | Gender | Categorical |
| ALTER | Person | Age | Categorical |
| SCHULAB | Person | Highest level of education | Categorical |
| BERUF | Person | Employment status | Categorical |
| FSPKW | Person | Driving license | Categorical |
| ZEITOPNV | Person | Seasonal ticket | Categorical |
| BAHNCARD | Person | Discount Railcard | Categorical |

**Note:** See **Table 3.4** for more details.

After selecting the variable and knowing all the potential treated and control IDs (see **Section 4.4.1** and **4.4.2**), using the "VLOOKUP" function in Excel, selected variables for each ID were assigned. However, all the cells in Excel files should have been analyzed to be compensated with R software and the MatchIT package.

### 4.4.3.2 Data manipulation

Three main manipulations and simplifications were done before importing data into R software. The first and foremost was to check all the empty cells among IDs because the MatchIT would automatically remove the ID if only one of its cells were empty. Reclassifying and merging variables were also the second and third manipulations.

Regarding the first point, some variables in the survey were deliberately filled with empty cells, not just because there was no answer. Therefore, it was necessary to check the meaning of an empty cell in all the variables. For example, an empty cell in the FSPKW column after 2016 means the individual does not have a driving license. Thus, the value was changed from blank to 0 to prevent removing ID by the MatchIT. On the other hand, the corresponding IDs of empty cells from EINKO column must be removed because of missing answers. Overall, the corresponding IDs of empty cells meaning no response were removed from potential treated and control groups.

In the second step of data manipulation, some of the classes of SCHULAB and BERUF variables were merged to improve the stability and robustness of the results. The fewer the classes, the higher the probability of matching between the treated and control groups in the MatchIT analyses. More specifically, the number of educational groups was reduced from seven to four classes by merging all the secondary school classes, resulting in individuals divided into pre-university, university, and no graduation classes, with also empty cells corresponding to the missing answers (**Table 4.9**).

**Table 4.9**

Reclassification of SCHULAB (Highest level of education) variable

| Year | Old classification | New classification |
|---|---|---|
| 2012 | 1. Secondary school, no vocational education<br>2. Secondary school, vocational education<br>3. General certificate of secondary education<br>4. University-entrance diploma, university of applied science diploma, university diploma<br>5. No graduation (yet)<br>Blank. No response | 1- 1.2.3<br>2- 4<br>3- 5<br>Blank- No response so Remove |
| 2013<br>2014<br>2015 | 1. Secondary school, no vocational education<br>2. Secondary school, vocational education<br>3. General certificate of secondary education<br>4. University-entrance diploma<br>5. University of applied science diploma, university diploma<br>6. No graduation (yet)<br>Blank. No response | 1- 1.2.3<br>2- 4.5<br>3- 6<br>Blank- No response so Remove |
| 2016<br>2017<br>2018 | 3- General certificate of secondary education<br>4- University-entrance diploma<br>5- University of applied science diploma, university diploma<br>6- No graduation (yet)<br>11- Secondary school<br>Blank- No response | 1- 3.11<br>2- 4.5<br>3- 6<br>Blank- No response so Remove |
| 2019<br>2020 | 3- General certificate of secondary education<br>4- University-entrance diploma<br>5- University of applied science diploma, university diploma<br>6- No graduation (yet)<br>1- Secondary school<br>Blank- No response | 1- 3.1<br>2- 4.5<br>3- 6<br>Blank- No response so Remove |

**Note:** Classifications of some variables in the MOP were occasionally changed from one wave to another.

Regarding employment status, shown in Error! Not a valid bookmark self-reference., the classes were reclassified from nine to five groups. To do that, apart from full-time workers, all the other types of workers merged. Similarly, all the non-employed individuals, including homemakers, children, and retired, were merged to make one class instead of three. Those with education status, such as students, were the exception by reclassifying in a separate class.

**Table 4.10**

Reclassification of BERUF (Employment status) variable

| Year | Old classification | New classification |
|---|---|---|
| 2012<br>2013<br>2014<br>2015<br>2016<br>2017<br>2018<br>2019<br>2020 | 1- Employed: full time<br>2- Employed: half time<br>3- Employed: temporarily unemployed<br>4- Education: in school, at university, in further education<br>5- Education: in vocational education<br>6- Not employed: homemaker<br>7- Not employed: retired<br>8- Not employed: child, in kindergarten<br>Blank- No response<br>9- Not employed: child, not in kindergarten | 0- 1<br>1- 2.3<br>2- 4.5<br>3- 6.7.8.0<br>Blank- No response so Remove |

**Note:** While MOP classifications occasionally changed from one wave to the next, BERUF classifications remained the same.

In the last part of data manipulation, two ZEITOPNV and BAHNCARD variables were merged. It was because both were related to individuals' public transport usage. Therefore, this merge was logically suitable when there was no significant difference between these two variables. Also, in the Matching method, the fewer variables, the better the chance of matching between treatment and control groups.

Accordingly, these two variables were adjusted to the one variable named P.T card. As shown in **Table 4.11**, if an individual reported having either the seasonal ticket or the rail card was joint to P.T card variable with the “1” value. Consequently, the probability of matching was substantially increased.

**Table 4.11**
Reclassification of ZEITOPNV, and BAHNCARD, and identification of their merged variable (P.T card)

| Year | Old classification | New classification (P.T card) |
|---|---|---|
| **ZEITOPNV** (Season ticket for public transport (7-day, monthly, annual ticket)) | | |
| 2012<br>2013<br>2014 | 1- Yes<br>2- NO<br>Blank- No response | |
| 2015<br>2016<br>2017<br>2018<br>2019<br>2020 | 1- Checked<br>Blank- Not checked | If ZEITOPNV = 1 or BAHNCARD = 1 so 1 otherwise 0 |
| **BAHNCARD** (Who has a valid "Deutsche Bahn" railcard?) | | |
| 2012<br>2013<br>2014 | 1- Yes<br>2- NO<br>Blank- No response | |
| 2015<br>2016<br>2017<br>2018<br>2019<br>2020 | 1- Checked<br>Blank- Not checked | |

**Note:** The new classification was actually for the new created variable called P.T card.

Having applied all the manipulations on the potential treated and control groups, eventually, the data were ready to be imported to R software for the matching analysis.

### 4.4.3.3 Final treated groups

Construction of treated groups began in **Section 4.4.1**, with pre-construction of car sharing members with some specific discards, resulting in identification of potential treated groups in each year.

Afterwards, in **Section 4.4.3.2** three manipulations were applied on the potential treatment groups, and **Table 4.12** is the final version of treated group prepared to be imported in R software for matching analyses. Indeed, these are input data of MatchIT.

The number of treated units were reduced in five over nine considered years after the final manipulations. The greatest change was in 2018, with a decrease of three users.

**Table 4.12**
Number of treated groups members, before and after final manipulations

| Year | Before | After |
|---|---|---|
| 2012 | 5 | 5 |
| 2013 | 12 | 12 |
| 2014 | 16 | 16 |
| 2015 | 17 | 16 |
| 2016 | 22 | 21 |
| 2017 | 31 | 31 |
| 2018 | 37 | 34 |
| 2019 | 41 | 40 |
| 2020 | 28 | 27 |

**Note:** "Before" are indeed data of **Table 4.4**.

### 4.4.3.4 Final potential control groups

Construction of control groups began in **Section 4.4.2** where two versions of potential control group were constructed for each year. Then in **Section 4.4.3.2** three manipulations were applied on the last version of potential control groups, and **Table 4.13** shows the final version of them which are prepared to be imported in R software for the matching analyses. Indeed, these are input data of MatchIT.

**Table 4.13**
Number of potential control groups members, before and after final manipulations

| Year | Before | After |
|---|---|---|
| 2012 | 581 | 541 |
| 2013 | 1057 | 932 |
| 2014 | 1251 | 1110 |
| 2015 | 1312 | 1177 |
| 2016 | 1403 | 1357 |
| 2017 | 1490 | 1448 |
| 2018 | 1497 | 1460 |
| 2019 | 1479 | 1449 |
| 2020 | 965 | 937 |

**Note:** "Before" are indeed data of potential control group_2 in **Table 4.7**.

# Chapter 5: DATA ANALYSIS AND RESULT

This chapter contains two main sections, matching analysis, and the results. All the steps done in MatchIT are described in the first section. The vehicle ownership patterns of treated and control units are recognized in the results part.

## 5.1 Matching analysis

### 5.1.1 Data preparation for the MatchIT package

After all discards (see **Sections 4.4.1** and **4.4.2**), and data manipulations (see **Section 4.4.3.2**), final treated and potential control groups were constructed including two separate files per wave. However, listing all the treated and potential control group IDs for each year in one Excel file was necessary for the matching process with MatchIT. Thus, this was the first step to be done. Nevertheless, the treated and control IDs needed to be identified in the list by a specific covariate. Thus, the second step was to add a column called "Treat" to the end of each unique Excel file created in the first step, by indicating 1 for treated IDs and 0 for the remaining. Finally, the last step was changing the Excel file format to CSV (Comma Separated Value).

The steps mentioned above were iterated up to 2020. Consequently, nine files were created (2012-2020). These files were prepared for the R software as input data for the matching method. As an example, only eight rows of the 2012 file are detailed in **Table 5.1** in which only five treated IDs versus 541 control units can be recognized from the "Treat" column.

**Table 5.1**
Input data of R software for the year 2012

| ID_der | RAUMTYP | HHGRO | P0_10 | EINKO | PKWHH | SEX | ALTER | SCHULAB | BERUF | FSPKW | P.T card | Treat |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 350574_2 | 1 | 2 | 0 | 8 | 1 | 1 | 4 | 2 | 1 | 1 | 1 | 1 |
| 370312_1 | 1 | 1 | 0 | 3 | 0 | 1 | 5 | 2 | 1 | 1 | 1 | 1 |
| 370568_1 | 1 | 1 | 0 | 5 | 1 | 2 | 5 | 2 | 1 | 1 | 1 | 1 |
| 370582_1 | 2 | 3 | 2 | 4 | 0 | 2 | 4 | 2 | 2 | 1 | 1 | 1 |
| 370781_1 | 1 | 1 | 0 | 6 | 0 | 1 | 4 | 2 | 1 | 1 | 1 | 1 |
| 350001_2 | 2 | 3 | 1 | 8 | 2 | 2 | 5 | 2 | 4 | 1 | 0 | 0 |
| 350006_1 | 2 | 5 | 2 | 8 | 2 | 1 | 4 | 2 | 1 | 1 | 0 | 0 |

### 5.1.2 Matching steps in R

The first step in R software was to import CSV files for each year one by one (All the codes are detailed in **Appendix B**). Afterward, it was necessary to check the structure or type of each data. In other words, the meaning of the value corresponding to each covariate must have been defined. For example, in the case of SEX, the value of 1 means male and 0 for female, and it must have been defined for R. In the same way, the value of EINKO (Net monthly income) should be clear, whether it refers to the amount in Euros or a category.

Qualitative or categorical is data that is divided into groups or categories. Both numerical and categorical data can take numerical values. It is noted that arithmetic operations cannot be performed on the values taken by categorical data. Thus, it was necessary to check the types and correct them based on our data set because R, by default, recognized all the numbers as integers which were wrong in this study due to the presence of many categorical data (The types of variables were mentioned in **Table 4.8**). Therefore, categorical variables were defined using the "as.factor" command in R. In the end, all the data types were defined, as seen in **Table 5.2**.

**Table 5.2**
The data structure of variables (year 2018) (R software outcome)

| Variable | Data type | Level |
|---|---|---|
| ID_der | Chr | -- |
| ID | int | -- |
| RAUMTYP | Factor | 5 |
| HHGRO | int | -- |
| P0_10 | int | -- |
| EINKO | Factor | 10 |
| PKWHH | int | -- |
| SEX | Factor | 2 |
| ALTER | Factor | 7 |
| SCHULAB | Factor | 3 |
| BERUF | Factor | 4 |
| FSPKW | Factor | 2 |
| P.T.card | Factor | 2 |
| Treat | Factor | 2 |

**Note**: "Chr" refers to character, "int" refers to integer and "Factor" to categorical data.

At this point, the "MatchIt" package (This package was described with more details in **Section 4.3.2**) was downloaded to be used for the matching process. R packages are extensions to the R statistical programming language. A package is a collection of code, data, and documentation that users of R can install, usually using a centralized software repository like CRAN (the Comprehensive R Archive Network). After loading the MatchIT package, the nearest neighbor method code was written. The ratio of five was selected, meaning that for each treated unit, there should be five matched IDs. This method was chosen among four main methods called exact, optimal, full, and nearest neighbor. The reasons for this selection were explained in **Section 4.3.2**.

In summary, the method was the neatest neighbor matching without replacement, the "distance" was propensity score estimated with logistic regression, and the target estimand (the purpose of the statistical analysis) was ATT. Indeed, ATT means average treatment effect on the treated when the outcome of treated are observed and controls are missing, like this study.

Having done all the matching steps, one of the results provided by MatchIT was the sample sizes (**Table 5.3**), where the size of matched, unmatched and discarded groups were shown for each wave separately. This table is the merged version of the MatchIT outcomes for all the years. For example, the number of IDs in the treated group for 2018 was 34, and considering the ratio of five, matched control group contains 170 units. Notably, there was no discarded sample, an advantage for the method selected (Nearest neighbor method) to do the matching. Moreover, at the bottom of the **Table 5.3**, total IDs and total unique IDs can be seen for each condition.

**Table 5.3**
Sample sizes of control and treated groups after matching. (Result of the MatchIT)

| Year | | ID's condition | | | |
|---|---|---|---|---|---|
| | | All | Matched | Unmatched | Discarded |
| 2012 | Control | 541 | 25 | 516 | 0 |
| | Treated | 5 | 5 | 0 | 0 |
| 2013 | Control | 932 | 60 | 872 | 0 |
| | Treated | 12 | 12 | 0 | 0 |
| 2014 | Control | 1110 | 80 | 1030 | 0 |
| | Treated | 16 | 16 | 0 | 0 |
| 2015 | Control | 1177 | 80 | 1097 | 0 |
| | Treated | 16 | 16 | 0 | 0 |
| 2016 | Control | 1357 | 105 | 1252 | 0 |
| | Treated | 21 | 21 | 0 | 0 |
| 2017 | Control | 1448 | 155 | 1293 | 0 |
| | Treated | 31 | 31 | 0 | 0 |
| 2018 | Control | 1460 | 170 | 1290 | 0 |
| | Treated | 34 | 34 | 0 | 0 |
| 2019 | Control | 1449 | 200 | 1249 | 0 |
| | Treated | 40 | 40 | 0 | 0 |
| 2020 | Control | 937 | 135 | 802 | 0 |
| | Treated | 27 | 27 | 0 | 0 |
| Total IDs | Control | 10411 | 1010 | 9401 | 0 |
| | Treated | 202 | 202 | 0 | 0 |
| Total unique IDs | Control | 4351 | 676 | 4183 | 0 |
| | Treated | 115 | 115 | 0 | 0 |

**Table 5.3** is just a summary of the results, but MatchIT provides some details information of the balance which are following.

#### 5.1.2.1 Details of the balance

Three tables and one plot are the outcomes to be discussed the balance in this section. It is noted that MatchIT provided outcomes separately for each wave. The results of each year are presented separately in the **Appendix C**, while only the results of 2018 are shown here as an example. The first outcome of R was the summary of balance for the original data imported into R, followed by the summary of balance for matched data. In **Table 5.4** and **Table 5.5**, these two summaries corresponding to 2018 are presented (2018 is just an example between 2012 and 2020).

Two terms called "Means Treated" and "Means Control" in these summary tables show means in these two groups and for each covariate. Normally, these two numbers are not close to each other for a covariate prior to matching. However, the goal is to reduce this gap by matching.

"Std. Mean Diff" is standardized mean differences. Indeed, this value refers to difference in mean outcome between groups divided by the standard deviation of outcome among participants. The ideal situation is when it is close to zero, when there is no difference between the groups. "Var. Ratio" refers to variance ratio. This ratio also called co-efficient of dispersion and is defined as the ratio of variance to mean. Furthermore, "eCDF Mean" and "eCDF Max" are about empirical cumulative density function. In other words, these two terms refer to the average and largest distance between the eCDFs of the covariate among the group.

It is also noted that the existence of more than one row in the summary tables for each covariate is because of the categorical data type. Indeed, the number of rows indicates the number of categories (levels) for each covariate.

Many values were far from their ideal in **Table 5.4** since a good balance is considered when values of standardized mean differences and empirical cumulative density function statistics are close to zero and values of variance ratio close to one. For example, regarding standardized mean differences, the value of "RAUMTYP1", "RAUMTYP2", "SCHULAB2", and "P.T card1" were 1,623, -1,269, 1,776, and 1,627, respectively. These values show a clear imbalance in the original imported data to R, and reflects different sociodemographic characteristics of car sharing users and non users that were mentioned in **Table 3.4**. For example, car sharing users are more subscribing to public transport with the "Meat Treated" value of 0.853 versus 0.277 in the "Mean Control" for the "P.T.card1". In the case of "SCHULAB2" which refers to a university degree (see **Table 4.9**), the value of the "Mean treated" is higher than the control groups. This difference shows the higher educational level of car sharing users compared to never car sharing members. Comparing "RAUMTYP1" and "RAUMTYP2" (see **Table 3.4** for the detailed description), it is noteworthy that car sharing users are more living in core regions of big cities rather than urban areas. The "Mean Treated" value is higher in the case of "RAUMTYP1", while the "Mean Control" value is almost ten times bigger in the "RAUMTYP2".

**Table 5.4**
Summary of balance for all data (Year 2018) (Result of the MatchIT)

| Covariate | Means Treated | Means Control | Std. Mean Diff | Var. Ratio | eCDF Mean | eCDF Max |
|---|---|---|---|---|---|---|
| distance | 0,298 | 0,016 | 1,043 | 24,320 | 0,464 | 0,797 |
| RAUMTYP1 | 0,912 | 0,451 | 1,623 | , | 0,460 | 0,460 |
| RAUMTYP2 | 0,029 | 0,244 | -1,269 | , | 0,214 | 0,214 |
| RAUMTYP3 | 0,059 | 0,197 | -0,585 | , | 0,138 | 0,138 |
| RAUMTYP4 | 0,000 | 0,057 | -0,248 | , | 0,057 | 0,057 |
| RAUMTYP5 | 0,000 | 0,051 | -0,235 | , | 0,051 | 0,051 |
| HHGRO | 2,206 | 2,091 | 0,114 | 0,867 | 0,044 | 0,095 |
| P0_10 | 0,412 | 0,287 | 0,168 | 1,195 | 0,031 | 0,115 |
| EINKO1 | 0,000 | 0,003 | -0,053 | , | 0,003 | 0,003 |
| EINKO2 | 0,029 | 0,045 | -0,089 | , | 0,015 | 0,015 |
| EINKO3 | 0,000 | 0,086 | -0,309 | , | 0,086 | 0,086 |
| EINKO4 | 0,059 | 0,127 | -0,291 | , | 0,069 | 0,069 |
| EINKO5 | 0,147 | 0,131 | 0,046 | , | 0,016 | 0,016 |
| EINKO6 | 0,206 | 0,111 | 0,235 | , | 0,095 | 0,095 |
| EINKO7 | 0,118 | 0,123 | -0,018 | , | 0,006 | 0,006 |
| EINKO8 | 0,059 | 0,093 | -0,143 | , | 0,034 | 0,034 |
| EINKO9 | 0,177 | 0,127 | 0,129 | , | 0,049 | 0,049 |
| EINKO10 | 0,206 | 0,155 | 0,126 | , | 0,051 | 0,051 |
| PKWHH | 0,412 | 1,316 | -1,289 | 0,659 | 0,129 | 0,546 |
| SEX1 | 0,677 | 0,496 | 0,386 | , | 0,181 | 0,181 |
| SEX2 | 0,324 | 0,504 | -0,386 | , | 0,181 | 0,181 |
| ALTER1 | 0,000 | 0,002 | -0,046 | , | 0,002 | 0,002 |
| ALTER2 | 0,088 | 0,027 | 0,217 | , | 0,062 | 0,062 |
| ALTER3 | 0,235 | 0,078 | 0,371 | , | 0,157 | 0,157 |
| ALTER4 | 0,265 | 0,190 | 0,168 | , | 0,074 | 0,074 |
| ALTER5 | 0,235 | 0,283 | -0,112 | , | 0,048 | 0,048 |
| ALTER6 | 0,147 | 0,225 | -0,221 | , | 0,078 | 0,078 |
| ALTER7 | 0,029 | 0,195 | -0,977 | , | 0,165 | 0,165 |
| SCHULAB1 | 0,059 | 0,469 | -1,741 | , | 0,410 | 0,410 |
| SCHULAB2 | 0,941 | 0,523 | 1,776 | , | 0,418 | 0,418 |
| SCHULAB3 | 0,000 | 0,008 | -0,092 | , | 0,008 | 0,008 |
| BERUF1 | 0,647 | 0,406 | 0,504 | , | 0,241 | 0,241 |
| BERUF2 | 0,147 | 0,193 | -0,128 | , | 0,045 | 0,045 |
| BERUF3 | 0,147 | 0,032 | 0,324 | , | 0,115 | 0,115 |
| BERUF4 | 0,059 | 0,369 | -1,319 | , | 0,310 | 0,310 |
| FSPKW0 | 0,000 | 0,044 | -0,217 | , | 0,044 | 0,044 |
| FSPKW1 | 1,000 | 0,956 | 0,217 | , | 0,044 | 0,044 |
| P.T.card0 | 0,147 | 0,723 | -1,627 | , | 0,576 | 0,576 |
| P.T.card1 | 0,853 | 0,277 | 1,627 | , | 0,576 | 0,576 |

**Table 5.5**
Summary of balance for matched data (Year 2018) (Result of the MatchIT)

| Covariate | Means Treated | Means Control | Std. Mean Diff | Var. Ratio | eCDF Mean | eCDF Max | Std. Pair Dist. |
|---|---|---|---|---|---|---|---|
| distance | 0,298 | 0,116 | 0,673 | 5,123 | 0,029 | 0,429 | 0,673 |
| RAUMTYP1 | 0,912 | 0,841 | 0,249 | , | 0,071 | 0,071 | 0,664 |
| RAUMTYP2 | 0,029 | 0,047 | -0,104 | , | 0,018 | 0,018 | 0,453 |
| RAUMTYP3 | 0,059 | 0,112 | -0,225 | , | 0,053 | 0,053 | 0,625 |
| RAUMTYP4 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| RAUMTYP5 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| HHGRO | 2,206 | 2,141 | 0,064 | 0,714 | 0,053 | 0,100 | 1,033 |
| P0_10 | 0,412 | 0,412 | 0,000 | 0,784 | 0,029 | 0,059 | 0,612 |
| EINKO1 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| EINKO2 | 0,029 | 0,041 | -0,070 | , | 0,012 | 0,012 | 0,348 |
| EINKO3 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| EINKO4 | 0,059 | 0,094 | -0,150 | , | 0,035 | 0,035 | 0,550 |
| EINKO5 | 0,147 | 0,177 | -0,083 | , | 0,029 | 0,029 | 0,714 |
| EINKO6 | 0,206 | 0,118 | 0,218 | , | 0,088 | 0,088 | 0,655 |
| EINKO7 | 0,118 | 0,112 | 0,018 | , | 0,006 | 0,006 | 0,712 |
| EINKO8 | 0,059 | 0,059 | 0,000 | , | 0,000 | 0,000 | 0,118 |
| EINKO9 | 0,177 | 0,165 | 0,031 | , | 0,012 | 0,012 | 0,802 |
| EINKO10 | 0,206 | 0,235 | -0,073 | , | 0,029 | 0,029 | 0,800 |
| PKWHH | 0,412 | 0,665 | -0,361 | 2,084 | 0,060 | 0,335 | 0,814 |
| SEX1 | 0,677 | 0,541 | 0,289 | , | 0,135 | 0,135 | 0,943 |
| SEX2 | 0,324 | 0,459 | -0,289 | , | 0,135 | 0,135 | 0,943 |
| ALTER1 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| ALTER2 | 0,088 | 0,053 | 0,124 | , | 0,035 | 0,035 | 0,498 |
| ALTER3 | 0,235 | 0,177 | 0,139 | , | 0,059 | 0,059 | 0,777 |
| ALTER4 | 0,265 | 0,247 | 0,040 | , | 0,018 | 0,018 | 0,920 |
| ALTER5 | 0,235 | 0,312 | -0,180 | , | 0,077 | 0,077 | 0,874 |
| ALTER6 | 0,147 | 0,159 | -0,033 | , | 0,012 | 0,012 | 0,698 |
| ALTER7 | 0,029 | 0,053 | -0,139 | , | 0,024 | 0,024 | 0,487 |
| SCHULAB1 | 0,059 | 0,077 | -0,075 | , | 0,018 | 0,018 | 0,525 |
| SCHULAB2 | 0,941 | 0,924 | 0,075 | , | 0,018 | 0,018 | 0,525 |
| SCHULAB3 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| BERUF1 | 0,647 | 0,653 | -0,012 | , | 0,006 | 0,006 | 0,997 |
| BERUF2 | 0,147 | 0,177 | -0,083 | , | 0,029 | 0,029 | 0,814 |
| BERUF3 | 0,147 | 0,082 | 0,183 | , | 0,065 | 0,065 | 0,581 |
| BERUF4 | 0,059 | 0,088 | -0,125 | , | 0,029 | 0,029 | 0,625 |
| FSPKW0 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| FSPKW1 | 1,000 | 1,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| P.T.card0 | 0,147 | 0,229 | -0,233 | , | 0,082 | 0,082 | 0,897 |
| P.T.card1 | 0,853 | 0,771 | 0,233 | , | 0,082 | 0,082 | 0,897 |

**Table 5.6**
Percent balance improvement (Year 2018) (Result of the MatchIT)

| Covariate | Std. Mean Diff | Var. Ratio | eCDF Mean | eCDF Max |
|---|---|---|---|---|
| distance | 35,5 | 48,8 | 93,8 | 46,1 |
| RAUMTYP1 | 84,7 | , | 84,7 | 84,7 |
| RAUMTYP2 | 91,8 | , | 91,8 | 91,8 |
| RAUMTYP3 | 61,6 | , | 61,6 | 61,6 |
| RAUMTYP4 | 100 | , | 100 | 100 |
| RAUMTYP5 | 100 | , | 100 | 100 |
| HHGRO | 43,6 | -136,2 | -20 | -4,8 |
| P0_10 | 100 | -37 | 5,7 | 48,7 |
| EINKO1 | 100 | , | 100 | 100 |
| EINKO2 | 22,1 | , | 22,1 | 22,1 |
| EINKO3 | 100 | , | 100 | 100 |
| EINKO4 | 48,5 | , | 48,5 | 48,5 |
| EINKO5 | -81,1 | , | -81,1 | -81,1 |
| EINKO6 | 7 | , | 7 | 7 |
| EINKO7 | -4,3 | , | -4,3 | -4,3 |
| EINKO8 | 100 | , | 100 | 100 |
| EINKO9 | 76 | , | 76 | 76 |
| EINKO10 | 42,4 | , | 42,4 | 42,4 |
| PKWHH | 72 | -76 | 53,8 | 38,6 |
| SEX1 | 25,1 | , | 25,1 | 25,1 |
| SEX2 | 25,1 | , | 25,1 | 25,1 |
| ALTER1 | 100 | , | 100 | 100 |
| ALTER2 | 42,6 | , | 42,6 | 42,6 |
| ALTER3 | 62,6 | , | 62,6 | 62,6 |
| ALTER4 | 76,2 | , | 76,2 | 76,2 |
| ALTER5 | -60,7 | , | -60,7 | -60,7 |
| ALTER6 | 85 | , | 85 | 85 |
| ALTER7 | 85,7 | , | 85,7 | 85,7 |
| SCHULAB1 | 95,7 | , | 95,7 | 95,7 |
| SCHULAB2 | 95,8 | , | 95,8 | 95,8 |
| SCHULAB3 | 100 | , | 100 | 100 |
| BERUF1 | 97,6 | , | 97,6 | 97,6 |
| BERUF2 | 35,2 | , | 35,2 | 35,2 |
| BERUF3 | 43,7 | , | 43,7 | 43,7 |
| BERUF4 | 90,5 | , | 90,5 | 90,5 |
| FSPKW0 | 100 | , | 100 | 100 |
| FSPKW1 | 100 | , | 100 | 100 |
| P,T,card0 | 85,7 | , | 85,7 | 85,7 |
| P,T,card1 | 85,7 | , | 85,7 | 85,7 |

All these values in **Table 5.4** were before the matching, and it was normal for a sample with this size to be imbalanced. However, these values were quite helpful in comparing with the matched sample summary (**Table 5.5**). A new column in this table called "Std. Pair Diff" displays each covariate's average absolute within-pair difference. When these values are small, a better balance is typically achieved.

Balance is far better after matching, as determined by the lower standardized mean differences and eCDF statistics in **Table 5.5**. About standardized mean differences, the two above-mentioned tables differ greatly. **Table 5.6** shows the balance improvements as percentages for 2018, with ten rows improving by 100 percent and ten more than 90 percent.

The "Love plot", a command in R, is also a simple way to summarize balance visually in R. As it can be seen in **Figure 5-1**, there was relatively poor balance before nearest neighbor matching in the year 2018, but the majority of covariates were within the 0.1 threshold after nearest neighbor matching. The white dots present absolute standardized mean difference before the matching, while the black ones correspond after matching. In other words, all the treated and control units are considered for the white dots, but the matched IDs and treated ones are considered in the black dots.

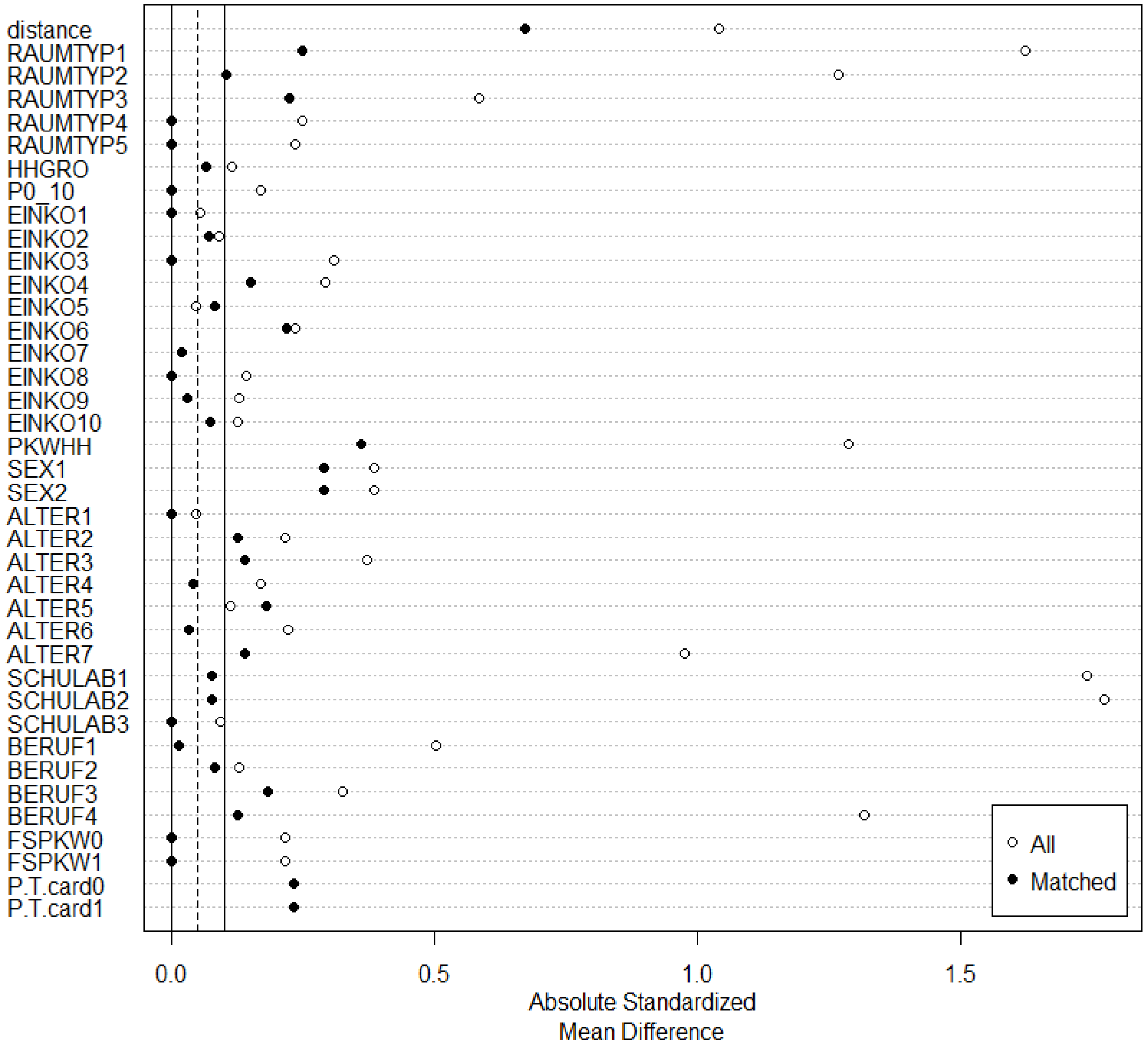


**Figure 5-1:** Love plot of the standardized mean differences (2018) (Result of the MatchIT)

## 5.2 Results

### 5.2.1 Vehicle ownership patterns of car sharing members

The identification of treated groups was explained in **Section 4.4.1**, and **Figure 4-1** represents the existence of 115 unique car sharing members. Car ownership status of these 115 members were also available in the MOP data set. Therefore, their car holding pattern was recognized, as shown in **Table 5.7** in which car sharing subscribers were divided into three main change patterns, “Increasing, “Decreasing”, and “No change” in their car ownership.

Furthermore, these 115 treated members were included in one of the three groups depending on their membership. The first group was “Always member” for individuals who were car sharing members in all the years they participated in the survey, and the second group was “Subscribed” for those who subscribed to a car sharing program in one of the waves in their presence in the survey. In contrast, the last group called “Unsubscribed” contains car sharing members who unsubscribed. Consequently, it was possible to determine their car ownership status in all the years presented in the survey, even before or after subscription. This could provide some ideas about the effects of car sharing subscriptions on their car ownership.

**Table 5.7**
Vehicle ownership pattern of car sharing members

| Change | Car holdings | | Always member | Subscribed | | | Unsubscribed | | | Total |
|---|---|---|---|---|---|---|---|---|---|---|
| | From | To | | One year before | Same year/ period | One year after | One year before | Same year/ period | One year after | |
| Increasing | 0 | 1 | 1 | _ | _ | _ | _ | 2 | _ | 3 |
| | 1 | 2 | _ | _ | 1 | _ | _ | 1 | _ | 2 |
| | > 2 | > 2+1 | – | – | – | – | – | – | – | 0 |
| Decreasing | 1 | 0 | 1 | _ | 3 | _ | _ | _ | _ | 4 |
| | 2 | 1 | _ | _ | 2 | _ | _ | _ | _ | 2 |
| | > 2 | > 2-1 | _ | _ | _ | _ | _ | _ | _ | 0 |
| No change | 0 | 0 | 33 | | 16 | | | 13 | | 62 |
| | 1 | 1 | 10 | | 10 | | | 14 | | 34 |
| | 2 | 2 | _ | | 5 | | | 2 | | 7 |
| | 3 | 3 | _ | | _ | | | 1 | | 1 |
| Total | | | 45 | | 37 | | | 33 | | 115 |

**Note**: “<2+1” in increasing pattern refers to more than two vehicle holders who bought one more. “>2-1” in decreasing pattern refers to more than two vehicle holders who sold one.

As it can be seen in **Table 5.7**, the majority of car sharing members had not changed their car ownership. They mostly had either no car or one car before and after their membership, 62 and 34 out of 115 IDs. Therefore, the first trend was about members without any change in their vehicle ownership, with over 80 percent of car sharing members. Among those who did not change their vehicle ownership status, the largest group was carless, and half of them were car sharing members in all the years interviewed, with 33 out of 62 IDs. This means a significant portion of car sharing members had no car and were still carless after subscribing to a car sharing program. Possibly, having a membership in a car sharing program made them unwill to purchase a new car.

Noticeably, those members included in either the “Always member” or “No change” categories showed a static behavior. However, in a dynamic process, we can take the best advantage of the statistical power of a panel dataset. Looking at the top-right of the table, dynamic behaviors in both car ownership and car sharing membership can be recognized. Although a few numbers of car sharing members were recorded in the MOP with an increase or decrease in their car ownership status, but the number of members who sold their vehicles was slightly higher than car buyers. Six car sharers sold one vehicle, while five purchased a new one. Moreover, eight members showed a trend affected by car sharing. Among five members showing an increasing trend in their car holdings, three of them increased their car ownership level in the same year of unsubscription to a car sharing program. In addition, five out of six members decreased their car holding levels when they joined a car sharing program.

It is also remarkable that only 1 member increased car ownership when subscribed. Another point is that only two out of 45 changed their car ownership levels without changing membership status, while nine out of 70 changed car ownership levels by subscribing or unsubscribing to a car sharing program. These nine cases proved that there are no observed time lags between car ownership and membership changes since all of them bought or sold their vehicles in the same year of changing membership status.

### 5.2.2 Vehicle ownership pattern of never car sharing members

The control groups were identified after the propensity score-based matching through MatchIT package in R software, as described in **Section 5.1.2**. The nearest neighbor matching method with the ratio of five was selected, and it means the MatchIT algorithm found 5 control matches for each treated unit.

All files containing each year's treated and matched IDs were exported from R software. These files look like **Table 5.8** (Only seven rows of the 2018 file are presented), in which the first row corresponds to the treated unit as the "Treat" column in 1, and all the others are matched IDs of the first row ID. As expected, there are five matches for each ID since the ratio in the matching method was set to five. Notably, the "distance" column shows the propensity score of the corresponding ID.

**Table 5.8**
The output file of the MatchIT (Year 2018)

| ID_der | RAUMTYP | HHGRO | P0_10 | EINKO | PKWHH | SEX | ALTER | SCHULAB | BERUF | FSPKW | P.T.card | Treat | distance |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 4501023080_1 | 1 | 2 | 0 | 9 | 0 | 1 | 7 | 2 | 4 | 1 | 1 | 1 | 0.138 |
| 4501026198_2 | 1 | 3 | 1 | 10 | 1 | 1 | 5 | 2 | 1 | 1 | 1 | 0 | 0.139 |
| 4701034034_2 | 3 | 2 | 0 | 10 | 1 | 1 | 6 | 2 | 1 | 1 | 0 | 0 | 0.062 |
| 8501022402_1 | 1 | 2 | 0 | 5 | 1 | 2 | 3 | 2 | 2 | 1 | 1 | 0 | 0.036 |
| 8511021806_2 | 1 | 2 | 0 | 10 | 1 | 1 | 5 | 2 | 1 | 1 | 1 | 0 | 0.132 |
| 8701035047_1 | 1 | 3 | 1 | 7 | 1 | 1 | 3 | 2 | 1 | 1 | 1 | 0 | 0.085 |

As a first step, matched IDs in different years were combined in one column removing duplication. This was done by checking the “Duplicate Values” command in Excel for two consecutive years, for example, 2012 and 2013. Then all the remaining IDs were listed under the 2012 column. The process was iterated for all remaining years up to 2020. In the end, a list of unique matched IDs in one column was obtained. Having merged all the years without duplication, considering one person might be interviewed in two or three years, 676 unique IDs span these nine years (2012-2020). The list of matched IDs is represented in **Appendix D**.

The next step was using the "VLOOKUP" function in Excel by referring to the original data, it was then possible to obtain car ownership (PKWHH) information of each of these 676 IDs in the different years. The result was a table with individuals who reported their car holdings each year. **Appendix D** details the vehicle ownership for each control ID over time.

It is noted that two IDs were discarded from the analysis because of their patterns. One was "4-1-0" and another "4-2-1". Although both IDs had a decreasing pattern, a significant change in their car holding led to removing these two individuals. Therefore, the final number of unique control IDs was 674.

In the end, car holding pattern of never car sharing members was recognized, as shown in **Table 5.9** in which individuals were divided into three main change patterns exactly like the car sharing members, increasing, decreasing, and no changes in car ownership. Clearly, there was no need to check for subscription of never car sharing members like treated units in **Table 5.7**.

**Table 5.9**
Vehicle ownership pattern of never car sharing members

| Change | Car holdings | | Number of IDs |
|---|---|---|---|
| | From | To | |
| Increasing | 0 | 1 | 12 |
| | 1 | 2 | 18 |
| | > 2 | > 2+1 | 2 |
| Decreasing | 1 | 0 | 7 |
| | 2 | 1 | 17 |
| | > 2 | > 2-1 | 3 |
| No change | 0 | 0 | 195 |
| | 1 | 1 | 375 |
| | 2 | 2 | 45 |
| | 3 | 3 | 0 |
| Total | | | 674 |

**Note**: "<2+1" in increasing pattern refers to more than two vehicle holders who bought one more. ">2-1" in decreasing pattern refers to more than two vehicle holders who sold one.

The total number of unique control IDs was 674. As was expected, like the treated groups, most control units did not change their car ownership over the years presented in the survey. Of this category, 375 individuals had only one vehicle in all the year asked, and 195 were carless. Notably, there is a big gap between these two groups and all the others. 45 out of 674 IDs reported two vehicle ownership in all the years without any change.

Looking at increasing and decreasing patterns, only around 60 individuals bought or sold a car, and most had either one or two cars. Over 30 IDs had an increasing pattern in car ownership, while 27 reported one car selling. Therefore, the higher number increased their vehicle holding than decreased.

### 5.2.3 Comparison of treated and control groups' vehicle ownership pattern

Since vehicle ownership patterns of treated and control groups were known, the last step was to compare them. Indeed, in this study, a control group was used to isolate car sharing effects and establish cause-and-effect relationship between car sharing and ownership. **Table 5.10** provides information about the percentage of car ownership patterns of individuals in the treated and control groups, since the two groups have different cardinality. As expected, the highest percentage in both groups is about non-car owners without change in their patterns. Of this category, as mentioned in **Section 5.2.1**, car sharing members mainly had no car in all the years interviewed, with around 54 percent of the total. In comparison, the majority in the case of the control group were individuals with one car in their households, which amounted to 56 percent. Consequently, the willingness of carless people to subscribe to one of the car sharing programs was higher than people owning cars.

Comparing partial totals in **Table 5.10**, it concludes that apart from those who did not change their car ownership during the survey period, car sharing members tend to sell their cars more than those who have never been car sharing members, amounting 5.2 versus 4 percent. Furthermore, car sharing subscribers have recorded less willingness to purchase a new vehicle than non-members, with 4.3 and 4.7 percent, respectively.

By inspection, it appears that the car sharing members bought less and sold more vehicles than never car sharing members, which is the expected outcome. However, we need to check if the differences between the treated and control groups shown in this table are statistically significant. Therefore, the Mann-Whitney U test was performed. This test is a no-parametric test used to compare any differences between two independent sample groups, and it assesses whether two samples (Treated and Control groups) are likely to derive from the same population. The null hypothesis was "The two populations are equal", and the alternate hypothesis was "The two populations are not equal". The alpha value was set at 0.05. This alpha value is the significance level indicating that there is a 5 percent chance of concluding that there is a difference when there is no actual difference.

As a result of Mann-Whitney U test, three p-values are shown in **Table 5.10**, meaning that the null hypothesis is correct and, thus, the two populations are equal. It is due to the fact that all p-values are greater than 0.05, and so the null hypothesis cannot be rejected. The p value indicates the degree of data compatibility with the null hypothesis. The lower the p-value, the greater the statistical significance of the observed difference.

**Table 5.10**

Comparison of vehicle ownership patterns between treated and control IDs (In percentage)

| Change | Car holdings From | Car holdings To | Treated Group % | Control Group % | *p*-value |
|---|---|---|---|---|---|
| Increasing | 0 | 1 | 2,6 | 1,8 | |
| | 1 | 2 | 1,7 | 2,7 | |
| | > 2 | > 2+1 | 0,0 | 0,3 | |
| | Total | | 4,3 | 4,7 | 0.268 |
| Decreasing | 1 | 0 | 3,5 | 1,0 | |
| | 2 | 1 | 1,7 | 2,5 | |
| | > 2 | > 2-1 | 0,0 | 0,4 | |
| | Total | | 5,2 | 4 | 0.198 |
| No change | 0 | 0 | 53,9 | 28,9 | |
| | 1 | 1 | 29,6 | 55,6 | |
| | 2 | 2 | 6,1 | 6,7 | |
| | 3 | 3 | 0,9 | 0,0 | |
| | Total | | 90,4 | 91,2 | 0.485 |
| | Total | | 100% | 100% | |

**Note**: “<2+1” in increasing pattern refers to more than two vehicle holders who bought one more. “>2-1” in decreasing pattern refers to more than two vehicle holders who sold one.

In conclusion, our data cannot statistically support that car sharing membership had an impact on the trends of car buying/selling. Nevertheless, this is probably due to the scarcity of observations in the treatment group (**Table 5.7**) rather than to an absence of effect. Therefore, in the following section we propose an exercise where the measured impact of car sharing membership on the changes in car ownership levels is projected in the whole universe (i.e., drivers in Germany).

## 5.3 Projection of car ownership impacts of car sharing un/subscription to the whole universe (German car drivers)

### 5.3.1 Survey weighting

As it can be seen in **Table 3.4**, an extrapolation factor (GEWHHPWO) in person level in the MOP data set is provided, so it was possible to weigh each individual based on the whole set of German drivers. One hundred fifteen treated units were found in this study (**Table 5.7**), and summing all their extrapolation factors, 3342766 was obtained. Accordingly, all the values in **Table 5.7** can be projected to the universe of German car drivers, leading to the following **Table 5.11**. Please note that numbers in the table are referring to data from 2012 until 2020 and only to a fraction of the sample that was selected according to the process described in **Section 4.4.1**, so they cannot be interpreted as counts on the number of car sharing members, subscribers or unsubscribers at any given time. In fact, it can for example be noted that the overall number of households that were observed to subscribe to car sharing (923,192) is smaller than those that unsubscribed (1,089,910), despite the steady growth over time of car sharing diffusion. These figures rather give an estimation on the proportion of households with car sharing members, subscribers or unsubscribers that changed or not changed their car ownership levels during these nine years in Germany.

**Table 5.11**
Vehicle ownership patterns of households with car sharing members in Germany (values from **Table 5.7** projected to the universe)

| Change | Car holdings From | Car holdings To | Always member | Subscribed: One year before | Subscribed: Same year/ period | Subscribed: One year after | Unsubscribed: One year before | Unsubscribed: Same year/ period | Unsubscribed: One year after | Total |
|---|---|---|---|---|---|---|---|---|---|---|
| Increasing | 0 | 1 | 305801 | _ | _ | _ | _ | 24040 | _ | 54621 |
| | 1 | 2 | _ | _ | 11115 | _ | _ | 15799 | _ | 26914 |
| | > 2 | > 2+1 | _ | _ | _ | _ | _ | _ | _ | 0 |
| Decreasing | 1 | 0 | 47640 | _ | 41531 | _ | _ | _ | _ | 89171 |
| | 2 | 1 | _ | _ | 49253 | _ | _ | _ | _ | 49253 |
| | > 2 | > 2-1 | _ | _ | _ | _ | _ | _ | _ | 0 |
| No change | 0 | 0 | 1018372 | | 544653 | | | 664766 | | 2227790 |
| | 1 | 1 | 233071 | | 197938 | | | 340142 | | 771150 |
| | 2 | 2 | _ | | 78702 | | | 40765 | | 119468 |
| | 3 | 3 | _ | | _ | | | 4399 | | 4399 |
| Total | | | 1329664 | | 923192 | | | 1089910 | | 3342766 |

As already noted in the previous paragraph, one intriguing aspect of these figures is that the four top-right panels of this table are not symmetric, in that the decrease of car ownership levels of those that subscribe to car sharing is larger than the increase of car ownership levels of those than unsubscribe, even considering lagged effects up to 1 year after car sharing subscription or unsubscription. Therefore, merely considering car sharing penetration rates at a given time point (i.e., the algebraic sum of car sharing subscribers and unsubscribers in all previous periods) to estimate car sharing impacts on car ownership might lead to biased results. Acknowledging such finding of the present research, the following sections will propose a set of scenarios where the impact of different patterns of car sharing subscriptions and unsubscriptions on car ownership levels in Germany will be explored.

### 5.3.2 Car sharing growth rate between 2021 and 2022

The car sharing growth rate in the last four years (2018-2022) was constantly increasing in Germany (see **Figure 3-1**), except in 2020, which was Covid year. The German car sharing fleet grew by around 16.12%, -4%, 22.31%, and 18% in these four years, with an average of almost 13%. Also, as mentioned in **Section 3.1**, there were 2,874,400 authorised drivers in Germany with German car sharing services as of January 1, 2021, which increased to 3,393,000 in 2022, i.e., an increase of 518,600 drivers (+18%).

On the basis of the analyses presented in the previous sections, the goal is now to understand how many vehicles were taken out from German streets between 2021 and 2022 due to this increase of car sharing membership. To do so, we need first to consider that the above increase is not considering multiple subscriptions, so that the same individual might be counted more than once. Then, car ownership levels are assessed at the household level, according to figures in **Table 5.11**, therefore multiple subscriptions by different drivers within the same household needs to be accounted as well.

Concerning the former issue, a survey run among a sample car sharing members in Germany in 2018 for the STARS project indicated that roughly 66.6% of the considered sample subscribed to only one kind of service (either free-floating, roundtrip or combined), whereas 27.7% to two different kinds of service and 5.7% to more than two different kinds of services (Bergstad, et al., 2018, p. 94, Table. 30). Unluckily, this datum cannot give a clear estimate on multiple subscriptions among German car sharing members for the following two reasons: (1) roundtrip users were oversampled and (2) multiple subscriptions for the same kind of service were not detected. Those two caveats however induce counterbalancing biases in the estimation of the real number of car sharing subscribers, since on the one hand roundtrip subscribers (who are only 23% of all car sharing subscribers according to bcs (2022)), are keener to subscribe also to free-floating services than vice-versa, thus leading to an overestimation of multiple subscriptions, whereas not detecting multiple subscriptions of the same kind of service is clearly an underestimation.

All in all, we decide to use the figures from the STARS survey and therefore we consider that the increase in the number of people having at least one car sharing subscription in German is equal to 518,600*0.666 = 345,388 individuals.

The next step is to estimate the number of households to which such individuals belong. From the MOP dataset, we recall that the overall number of surveyed car sharing members was 233 (**Section 4.4.1**), that belonged to 195 different households. Therefore, we have an average of 233/195 = 1.19 car sharing members in each household where at least one car sharing member is present. To sum up, the estimated increase in the number of households where at least one car sharing member is present between 2021 and 2022 is equal to 345,388/1.19 = 290,242 households.

### 5.3.3 Patterns of car sharing growth and related projections on car ownership impacts in Germany

In order to estimate the number of cars that were taken out of streets in Germany in 2021 in relation with (but not necessarily as a consequence of) the annual car sharing growth, it is now necessary to revert to figures in the top right corner of **Table 5.11**. We can therefore observe that 41,531+49,253-11,115 = 79,669 cars are taken out of streets when 923,192 households subscribe, whereas 24,040+15,799 = 39,839 cars are added in the streets when 1,089,910 households unsubscribe. Thus, we define a car sharing subscription-vehicle ownership substitution rate equal to SR = 79669/923192 = 0.086 less private vehicles for each household subscribing to car sharing, and a car sharing unsubscription-vehicle ownership complementarity rate equal to CR = 39839/1089910 = 0.036 more private vehicles for each household unsubscribing to car sharing.

Given the above discussed limitations of **Table 5.11**, row and moreover column totals of that table are not representing real proportions of car sharing (un)subscribers in any given period. Therefore, we cannot consider them to infer the proportion of subscriptions and unsubscriptions that lead to the increase of households where at least one car sharing member is present that was estimated in the previous subsection (i.e., 290,242 households).

Therefore, the exercise that we take here is to show through a sensitivity analysis how different proportions of subscriptions and unsubscriptions that are all leading to the same net increase (i.e., +290,242 households) could lead to different car ownership impacts related to the expansion of car sharing. For example, considering that the net increase is only due to new subscriptions and that nobody unsubscribed, we can estimate that 0.086*290,242 = 24,961 private cars have been taken out of the streets during 2021. More in general, assuming that the number of households that unsubscribed in Germany in 2021 is equal to $x$, the formula (**Equation (1)**) that is giving the number of cars taken out of streets as a function of $x$, considering a constant and overall increase of car sharing diffusion equal to 290,242 is the following:

$$\text{Substituted cars} = SR * (290{,}242+x) - CR * x \quad (1)$$

Where SR and CR equal to 0.086 and 0.036, leading to the following linear relationship **Equation (2)**:

$$\text{Substituted cars} = 24961 + 0.05 * x \quad (2)$$

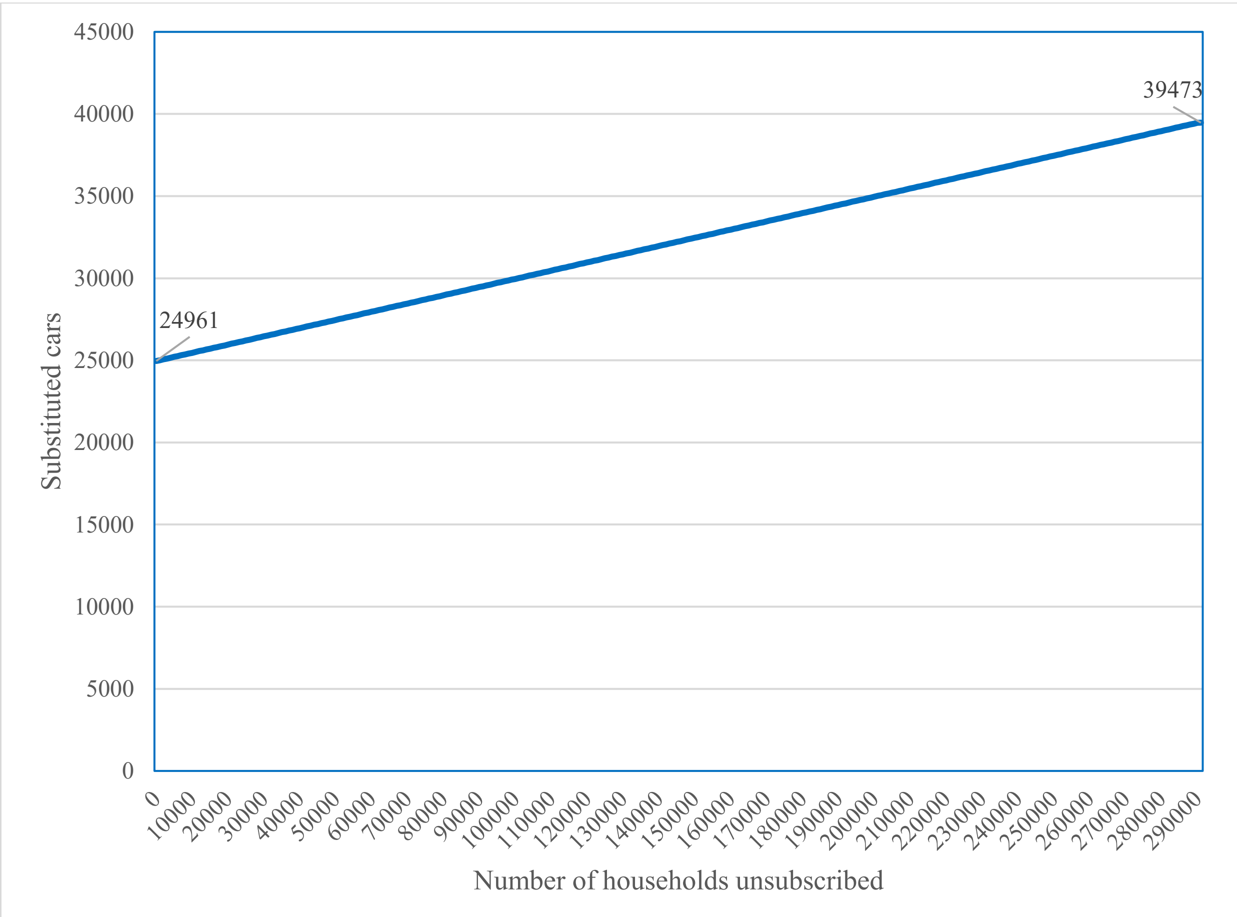


**Figure 5-2:** Sensitivity analysis on the patterns of car sharing growth in Germany in 2021

**Figure 5-2** shows how the number of substituted cars changes according to x. It has an increasing trend starting from zero number of households unsubscribed to 290,242 households, with 24,961 and 39,473 substituted cars, respectively. Notably, we assumed a constant annual increase in car sharing households equal to 290,242 in 2021. Therefore, the number of cars taken off the roads increases when we increase the number of households unsubscribed, and, as a consequence, the number of households that subscribed since SR>CR.

The above sensitivity analysis has clarified the impact on car ownership of different mixes of subscriptions and unsubscriptions that are all consistent with the estimated increase of households with car sharing members in Germany during 2021. We can approximatively assume that, in relative terms, such increase is the same as the +18% increase of authorized drivers that was mentioned at the beginning of the previous section. As a final exercise, we would like to extend our results by looking at the car ownership impacts of different car sharing growing trends (ranging from -5% to +30%), for different combinations of subscriptions and unsubscriptions. These results are presented in **Table 5.12.**

**Table 5.12**
Impacts of different growth rates of car sharing on car ownership assuming different subscription /unsubscription patterns

| Increase | | Pattern 1 | Pattern 2 | Pattern 3 | Pattern 4 | Pattern 5 | Pattern 6 |
|---|---|---|---|---|---|---|---|
| | Subscriptions | 0 | 15000 | 30000 | 45000 | 60000 | 75000 |
| -5% | Unsubscriptions | 80623 | 95623 | 110623 | 125623 | 140623 | 155623 |
| | Decrease of private cars | -2902 | -2152 | -1402 | -652 | 98 | 848 |
| | Subscriptions | 0 | 60000 | 120000 | 180000 | 240000 | 300000 |
| 0% | Unsubscriptions | 0 | 60000 | 120000 | 180000 | 240000 | 300000 |
| | Decrease of private cars | 0 | 3000 | 6000 | 9000 | 12000 | 15000 |
| | Subscriptions | 80623 | 95623 | 110623 | 125623 | 140623 | 155623 |
| 5% | Unsubscriptions | 0 | 15000 | 30000 | 45000 | 60000 | 75000 |
| | Decrease of private cars | 6934 | 7684 | 8434 | 9184 | 9934 | 10684 |
| | Subscriptions | 161246 | 191246 | 221246 | 251246 | 281246 | 311246 |
| 10% | Unsubscriptions | 0 | 30000 | 60000 | 90000 | 120000 | 150000 |
| | Decrease of private cars | 13867 | 15367 | 16867 | 18367 | 19867 | 21367 |
| | Subscriptions | 241868 | 286868 | 331868 | 376868 | 421868 | 466868 |
| 15% | Unsubscriptions | 0 | 45000 | 90000 | 135000 | 180000 | 225000 |
| | Decrease of private cars | 20801 | 23051 | 25301 | 27551 | 29801 | 32051 |
| | Subscriptions | 290242 | 350242 | 410242 | 470242 | 530242 | 590242 |
| 18% | Unsubscriptions | 0 | 60000 | 120000 | 180000 | 240000 | 300000 |
| (2021 increase) | Decrease of private cars | 24961 | 27961 | 30961 | 33961 | 36961 | 39961 |
| | Subscriptions | 322491 | 382491 | 442491 | 502491 | 562491 | 622491 |
| 20% | Unsubscriptions | 0 | 60000 | 120000 | 180000 | 240000 | 300000 |
| | Decrease of private cars | 27734 | 30734 | 33734 | 36734 | 39734 | 42734 |
| | Subscriptions | 403114 | 478114 | 553114 | 628114 | 703114 | 778114 |
| 25% | Unsubscriptions | 0 | 75000 | 150000 | 225000 | 300000 | 375000 |
| | Decrease of private cars | 34668 | 38418 | 42168 | 45918 | 49668 | 53418 |
| | Subscriptions | 483737 | 573737 | 663737 | 753737 | 843737 | 933737 |
| 30% | Unsubscriptions | 0 | 90000 | 180000 | 270000 | 360000 | 450000 |
| | Decrease of private cars | 41601 | 46101 | 50601 | 55101 | 59601 | 64101 |

As it can be seen in **Table 5.12**, nine different car sharing growth trends, ranging from -5 to 30%, are considered, and for each increase, six patterns are calculated. It starts with "Pattern 1" in which the corresponding growth percentage is considered and continues accordingly by increasing the number of un/subscriptions to the next patterns. In "Pattern 1", all the growth is added either to subscriptions or unsubscriptions based on the percentage (minus for unsubscriptions and plus for the subscriptions). From "Pattern 2" to the end, the same number of users are added to subscriptions and unsubscriptions to calculate the "Decrease of private cars". All the numbers rose from the first pattern to the end, leading to more private cars being removed from the streets.

It is also possible to study a generalized version of **Equation (1)**, not considering the net increase of car sharing observed for Germany in 2022 (i.e. 290,242 households), to calculate the net variation in the number of cars in that country (car fleet balance, where positive values indicate an increase of the number of cars), see **Equation (3)**.

$$\text{Car fleet balance} = CR*u - SR*s \tag{3}$$

where *s* and *u* are respectively the number of household subscriptions and unsubscriptions.

The below **Table 5.13** shows also numerically the number of substituted cars calculated based on the generalized equation. It is noted that values on the main diagonal (in bold) represent an unchanged number of households overall subscribing to car sharing, however the net car fleet balance is still positive. An increase of private cars can be seen only with a sharp decrease in the number of household with at least one car sharing member (numbers in red).

**Table 5.13**
Number of substituted cars based on **Equation (3)**

| Unsubscribing | Subscribing | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0 | 100000 | 200000 | 300000 | 400000 | 500000 | 600000 | 700000 | 800000 | 900000 | 1000000 |
| 0 | **0** | -8600 | -17200 | -25800 | -34400 | -43000 | -51600 | -60200 | -68800 | -77400 | -86000 |
| 100000 | 3600 | **-5000** | -13600 | -22200 | -30800 | -39400 | -48000 | -56600 | -65200 | -73800 | -82400 |
| 200000 | 7200 | -1400 | **-10000** | -18600 | -27200 | -35800 | -44400 | -53000 | -61600 | -70200 | -78800 |
| 300000 | 10800 | 2200 | -6400 | **-15000** | -23600 | -32200 | -40800 | -49400 | -58000 | -66600 | -75200 |
| 400000 | 14400 | 5800 | -2800 | -11400 | **-20000** | -28600 | -37200 | -45800 | -54400 | -63000 | -71600 |
| 500000 | 18000 | 9400 | 800 | -7800 | -16400 | **-25000** | -33600 | -42200 | -50800 | -59400 | -68000 |
| 600000 | 21600 | 13000 | 4400 | -4200 | -12800 | -21400 | **-30000** | -38600 | -47200 | -55800 | -64400 |
| 700000 | 25200 | 16600 | 8000 | -600 | -9200 | -17800 | -26400 | **-35000** | -43600 | -52200 | -60800 |
| 800000 | 28800 | 20200 | 11600 | 3000 | -5600 | -14200 | -22800 | -31400 | **-40000** | -48600 | -57200 |
| 900000 | 32400 | 23800 | 15200 | 6600 | -2000 | -10600 | -19200 | -27800 | -36400 | **-45000** | -53600 |
| 1000000 | 36000 | 27400 | 18800 | 10200 | 1600 | -7000 | -15600 | -24200 | -32800 | -41400 | **-50000** |

# Chapter 6: CONCLUSIONS

Car sharing is one of the shared mobility services that can potentially reduce private car usage and car ownership and encourage individuals to use different modes of transport. This thesis investigates the impact of car sharing on car ownership. We perform the analysis using data from the 2012-2020 (nine waves) German Mobility Panel (MOP), an unbalanced and rotating panel survey conducted annually in Germany. The sample size was 1913 individuals in 2012, then growing annually, reaching 3461 respondents in 2020. Notably, car sharing members were only 0.63% (12 members) up to 2.40% (83 members) of the total interviewers from 2012 to 2020. Regarding car ownership, the household car holding status percentage was almost similar during the survey period (2012-2020). Indeed, around 50 percent of the household in all the years had only one vehicle, and then two-car owners were almost 25 percent of the households. Less than 15 percent of households owned no vehicle in all the waves.

We use the matching method to compare units with the same values of the covariates but different treatment values. Thus, it was necessary to construct two groups of control (never car sharing members) and treated (car sharing members) units. This analysis uses longitudinal panel data to prevent recall bias. Moreover, propensity-score-based matching is used to help control self-selection bias due to differences in observed socio-demographic characteristics between respondents. The treatment and control groups are identified to isolate car sharing membership effect, one necessary step towards establishing causal relationships. We select the nearest neighbor matching method with a ratio of five for this thesis. Both control and treated units are estimated using logistic regression using R software. The considered variables are the following:

- RAUMTYP: Type of region based on inhabitants and location
- HHGRO: Number of people permanently living in the household
- P0_10: Number of children under the age 10
- EINKO: Net household income per month
- PKWHH: Cars permanently available in the household
- SEX: Gender
- ALTER: Age
- SCHULAB: The highest education level
- BERUF: Employment status
- FSPKW: Car driving license
- P.T.card: Public transport card

One hundred fifteen unique car sharing members with at least two years of information are found in the dataset. The majority of them had not changed their car ownership. They mostly had either no car or one car before and after their membership, respectively 62 and 34 out of 115. Therefore, the first trend was about members without any change in their vehicle ownership, with over 80 percent of car sharing members. Although a few car sharing members were recorded in the MOP with an increase or decrease in their car ownership status, the number of members who sold their vehicles was slightly higher than car buyers. Six car sharers sold one vehicle, while five purchased a new one. Moreover, eight members showed a trend affected by car sharing. Among five members showing an increasing trend in their car holdings, three of them increased their car ownership level in the same year of unsubscription to a car sharing program. In addition, five out of six members decreased their car holding levels when they joined a car sharing program.

Four thousand three hundred fifty-one unique control units with at least one year of information are found. 674 of them were matched to treated units after the matching procedure. As was expected, like the treated groups, most control units did not change their car ownership over the years presented in the survey. Of this category, 375 individuals had only one vehicle in all the years asked, and 195 were carless. Notably, there is a big gap between these two groups and all the others. 45 out of 674 IDs reported two vehicle ownership in all the years without any change. Of increasing and decreasing patterns, only around 60 individuals bought or sold a car, and most had one or two cars. Over 30 IDs had an increasing pattern in car ownership, while 27 reported one car selling. Therefore, the higher number increased their vehicle holding than decreased.

In both treated and control groups, most members did not change their car ownership level over the years recorded. 4.7% of the control groups purchased a new car, but 4.3% of the treated ones. Oppositely, more car sharing users foregone a vehicle than the controls, amounting to 5.2% and 4%. In conclusion, our data cannot statistically support that car sharing membership impacted the trends of car selling/buying, not because of existing no effect but most likely because of the scarcity of observations.

Finally, the projection of car ownership impacts of car sharing un/subscription to the whole universe (German car drivers) was performed. The cumulative number of observed households with the presence of a car sharing member in all the years recorded amounted to 1,329,664 when expanded to the universe. The projected total number of users that were observed while unsubscribing was 1,089,910, whereas 923,192 expanded subscribers to the universe were found.

Considering such figures, it was possible to estimate how many vehicles were taken out from German streets between 2021 and 2022, considering that the increase in the number of people having at least one car sharing subscription in German is equal to 345,388 individuals. An average of 1.19 car sharing members in each household was present, and the estimated increase in subscribing households between 2021 and 2022 was calculated to be 290,242. Notably, 0.086 fewer private vehicles for each household subscribing to car sharing and 0.036 more private vehicles for each household unsubscribing to car sharing were estimated. Using sensitivity analysis and having fixed the above-mentioned increase of subscribing households (290,242), depending on the balance between subscribed and unsubscribed households, the number of substituted cars ranges from 24,961 to 39,437 cars between 2021 and 2022.

We also extended our results by looking at the car ownership impacts of different car sharing growing trends (ranging from -5% to +30%), for different combinations of subscriptions and unsubscriptions. It resulted in a increasing trend among all the numbers. The higher growth percentage and higher number of un/subscriptions, the higher number of substituted cars.

As a final exercise, we introduced a generalized equation to estimate car fleet balance by considering only the number of household subscriptions and unsubscriptions. As a result, an increase in private cars can be seen only with a sharp decrease in the number of households with at least one car sharing member.

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# Appendices

## Appendix A
## Car ownership level and car sharing status of unique car sharing IDs over time (2012-2020)

233 unique car sharing members were spanning these nine years (2012-2020). The number in the PKWHH columns refers to the number of private cars for each ID. In the PKWCS columns, there is either 0 or 1, in which zero refers to non_member, and one refers to being a member of any car sharing company. Notably, discarded patterns mentioned in **Section 4.4.1** are shadowed in grey.

**Table A.A–1**
Details of car ownership level and car sharing status of all the 233 unique car sharing IDs over time.

| # | ID_der | PKWHH | | | | | | | | | PKWCS | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 |
| 1 | 330335_1 | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ |
| 2 | 330566_3 | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ |
| 3 | 330646_1 | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ |
| 4 | 350574_1 | 1 | 0 | _ | _ | _ | _ | _ | _ | _ | 1 | 1 | _ | _ | _ | _ | _ | _ | _ |
| 5 | 350574_2 | 1 | 0 | _ | _ | _ | _ | _ | _ | _ | 1 | 1 | _ | _ | _ | _ | _ | _ | _ |
| 6 | 370117_1 | 2 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ |
| 7 | 370312_1 | 0 | _ | 0 | _ | _ | _ | _ | _ | _ | 1 | _ | 0 | _ | _ | _ | _ | _ | _ |
| 8 | 370340_1 | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ |
| 9 | 370568_1 | 1 | 1 | 1 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ | _ | _ |
| 10 | 370582_1 | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 1 | 0 | _ | _ | _ | _ | _ | _ |
| 11 | 370781_1 | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 0 | 0 | _ | _ | _ | _ | _ | _ |
| 12 | 730036_2 | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ |
| 13 | 350198_2 | 2 | 1 | _ | _ | _ | _ | _ | _ | _ | 0 | 1 | _ | _ | _ | _ | _ | _ | _ |
| 14 | 350385_1 | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ |
| 15 | 3900000350_1 | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ | _ |
| 16 | 3900000780_1 | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ | _ |
| 17 | 3900000988_1 | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ |
| 18 | 3900000988_2 | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ |
| 19 | 3900000995_2 | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 1 | 0 | _ | _ | _ | _ | _ |
| 20 | 3910001305_1 | _ | 1 | 2 | 2 | _ | _ | _ | _ | _ | _ | 1 | 0 | 0 | _ | _ | _ | _ | _ |
| 21 | 3910003085_1 | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ |
| 22 | 3910003099_1 | _ | 0 | 1 | _ | _ | _ | _ | _ | _ | _ | 1 | 1 | _ | _ | _ | _ | _ | _ |
| 23 | 3910003103_1 | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ | _ |
| 24 | 7900000530_1 | _ | 0 | 0 | _ | _ | _ | _ | _ | _ | _ | 1 | 1 | _ | _ | _ | _ | _ | _ |
| 25 | 7910002939_2 | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ | _ |
| 26 | 370095_1 | 1 | _ | 1 | _ | _ | _ | _ | _ | _ | 0 | _ | 1 | _ | _ | _ | _ | _ | _ |

| # | ID_der | PKWHH | | | | | | | | | PKWCS | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 |
| 27 | 370113_1 | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 0 | 0 | 1 | _ | _ | _ | _ | _ | _ |
| 28 | 3900000368_2 | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 0 | 1 | 1 | _ | _ | _ | _ | _ |
| 29 | 3900000874_1 | _ | 2 | 2 | 2 | _ | _ | _ | _ | _ | _ | 0 | 1 | 0 | _ | _ | _ | _ | _ |
| 30 | 3900001063_1 | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ |
| 31 | 3910003035_1 | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ |
| 32 | 4101003717_1 | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ |
| 33 | 4118000465_1 | _ | _ | 0 | 0 | _ | _ | _ | _ | _ | _ | _ | 1 | 1 | _ | _ | _ | _ | _ |
| 34 | 4118000465_2 | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ |
| 35 | 4118000941_2 | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ |
| 36 | 4118001112_1 | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ |
| 37 | 4118001174_1 | _ | _ | 0 | 0 | _ | _ | _ | _ | _ | _ | _ | 1 | 1 | _ | _ | _ | _ | _ |
| 38 | 7910000086_1 | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ |
| 39 | 7910001333_1 | _ | _ | 0 | 0 | _ | _ | _ | _ | _ | _ | _ | 1 | 1 | _ | _ | _ | _ | _ |
| 40 | 8101002582_1 | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 0 | 1 | _ | _ | _ | _ |
| 41 | 8101004249_2 | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ |
| 42 | 8111000088_1 | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ |
| 43 | 8111000088_2 | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ |
| 44 | 3900000368_1 | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 0 | 0 | 1 | _ | _ | _ | _ | _ |
| 45 | 3900000602_1 | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 0 | 0 | 1 | _ | _ | _ | _ | _ |
| 46 | 4101001671_1 | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ | _ | _ | 0 | 1 | 1 | _ | _ | _ | _ |
| 47 | 4118000280_1 | _ | _ | 0 | 1 | 1 | _ | _ | _ | _ | _ | _ | 0 | 1 | 0 | _ | _ | _ | _ |
| 48 | 4301012188_1 | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 1 | 0 | _ | _ | _ |
| 49 | 4301013351_2 | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ |
| 50 | 4301013900_1 | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ |
| 51 | 4311010227_2 | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ |
| 52 | 4311010488_2 | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ |
| 53 | 8101005109_1 | _ | _ | 1 | 1 | 2 | _ | _ | _ | _ | _ | _ | 0 | 1 | 0 | _ | _ | _ | _ |
| 54 | 8301014408_2 | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 0 | 0 | _ | _ | _ |
| 55 | 8311010369_1 | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ |
| 56 | 4301013598_1 | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ |
| 57 | 4301013598_2 | _ | _ | _ | _ | 1 | 1 | _ | _ | _ | _ | _ | _ | _ | 1 | 0 | _ | _ | _ |
| 58 | 4311010291_1 | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 0 | 1 | 1 | _ | _ | _ |
| 59 | 4311011122_1 | _ | _ | _ | 2 | 2 | 2 | _ | _ | _ | _ | _ | _ | 0 | 1 | 1 | _ | _ | _ |
| 60 | 4311012485_2 | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ | _ | _ | 0 | 1 | 1 | _ | _ | _ |
| 61 | 4501023498_1 | _ | _ | _ | _ | 0 | _ | 0 | _ | _ | _ | _ | _ | _ | 1 | _ | 1 | _ | _ |
| 62 | 4501023718_1 | _ | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ |
| 63 | 4501024192_1 | _ | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ |
| 64 | 4501024192_2 | _ | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ |
| 65 | 4501024389_3 | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ |
| 66 | 4501026026_2 | _ | _ | _ | _ | 1 | 1 | _ | _ | _ | _ | _ | _ | _ | 1 | 0 | _ | _ | _ |
| 67 | 4501026205_1 | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ |
| 68 | 4511020869_1 | _ | _ | _ | _ | 1 | 1 | _ | _ | _ | _ | _ | _ | _ | 1 | 1 | _ | _ | _ |

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| | | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 |
| 69 | 4511020887_1 | _ | _ | _ | _ | 1 | 1 | _ | _ | _ | _ | _ | _ | _ | 1 | 0 | _ | _ | _ |
| 70 | 4511021510_1 | _ | _ | _ | _ | 0 | _ | 0 | _ | _ | _ | _ | _ | _ | 1 | _ | 1 | _ | _ |
| 71 | 4511021510_2 | _ | _ | _ | _ | 0 | _ | 0 | _ | _ | _ | _ | _ | _ | 1 | _ | 1 | _ | _ |
| 72 | 8111000468_2 | _ | _ | 2 | _ | 1 | _ | _ | _ | _ | _ | _ | 0 | _ | 1 | _ | _ | _ | _ |
| 73 | 8111000693_1 | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 0 | 0 | 1 | _ | _ | _ | _ |
| 74 | 8501025150_1 | _ | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 0 | 0 | _ | _ |
| 75 | 4301013541_1 | _ | _ | _ | 2 | 2 | 2 | _ | _ | _ | _ | _ | _ | 0 | 0 | 1 | _ | _ | _ |
| 76 | 4301013615_1 | _ | _ | _ | 1 | 2 | 1 | _ | _ | _ | _ | _ | _ | 0 | 0 | 1 | _ | _ | _ |
| 77 | 4311010004_1 | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ | _ | _ | 0 | 0 | 1 | _ | _ | _ |
| 78 | 4311010488_1 | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 0 | 0 | 1 | _ | _ | _ |
| 79 | 4311012485_1 | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ | _ | _ | 0 | 0 | 1 | _ | _ | _ |
| 80 | 4501022854_1 | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ |
| 81 | 4501022859_1 | _ | _ | _ | _ | 1 | 0 | _ | _ | _ | _ | _ | _ | _ | 0 | 1 | _ | _ | _ |
| 82 | 4501023719_1 | _ | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 0 | 1 | 1 | _ | _ |
| 83 | 4511020396_1 | _ | _ | _ | _ | _ | 1 | 1 | _ | _ | _ | _ | _ | _ | _ | 1 | 0 | _ | _ |
| 84 | 4511020482_1 | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ | _ | _ | 0 | 1 | 0 | _ | _ |
| 85 | 4511020803_1 | _ | _ | _ | _ | _ | 1 | 1 | _ | _ | _ | _ | _ | _ | _ | 1 | 0 | _ | _ |
| 86 | 4701032260_1 | _ | _ | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 1 | 0 | _ |
| 87 | 4701032377_2 | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ |
| 88 | 4701032627_1 | _ | _ | _ | _ | _ | 1 | 1 | _ | _ | _ | _ | _ | _ | _ | 1 | 0 | _ | _ |
| 89 | 4701033025_1 | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ |
| 90 | 4701033073_2 | _ | _ | _ | _ | _ | 2 | 2 | 2 | _ | _ | _ | _ | _ | _ | 1 | 1 | 0 | _ |
| 91 | 4701033576_1 | _ | _ | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ |
| 92 | 4701034144_1 | _ | _ | _ | _ | _ | 0 | _ | 1 | _ | _ | _ | _ | _ | _ | 1 | _ | 0 | _ |
| 93 | 4701034144_2 | _ | _ | _ | _ | _ | 0 | _ | 1 | _ | _ | _ | _ | _ | _ | 1 | _ | 1 | _ |
| 94 | 4701034508_1 | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ |
| 95 | 4701034547_1 | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ | _ | _ | 1 | 0 | 0 | _ |
| 96 | 4701034946_1 | _ | _ | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ |
| 97 | 4701035006_1 | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ |
| 98 | 4711030062_1 | _ | _ | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ |
| 99 | 4711030062_2 | _ | _ | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 1 | 0 | _ |
| 100 | 4711030077_1 | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ | _ | _ | 1 | 0 | 0 | _ |
| 101 | 4711030077_2 | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ | _ | _ | 1 | 0 | 0 | _ |
| 102 | 4711030198_1 | _ | _ | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 0 | 0 | _ |
| 103 | 4711030501_1 | _ | _ | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 0 | 1 | _ |
| 104 | 8301012304_1 | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 0 | 0 | 1 | _ | _ | _ |
| 105 | 8311015326_1 | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 0 | 0 | 1 | _ | _ | _ |
| 106 | 8501026108_1 | _ | _ | _ | _ | 0 | 0 | 1 | _ | _ | _ | _ | _ | _ | 0 | 1 | 0 | _ | _ |
| 107 | 8501026108_2 | _ | _ | _ | _ | 0 | 0 | 1 | _ | _ | _ | _ | _ | _ | 0 | 1 | 0 | _ | _ |
| 108 | 8701033348_1 | _ | _ | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ |
| 109 | 8701033701_1 | _ | _ | _ | _ | _ | 2 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ |
| 110 | 8701033701_2 | _ | _ | _ | _ | _ | 2 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ |

| # | ID_der | PKWHH | | | | | | | | | PKWCS | | | | | | | | |
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| | | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 |
| 111 | 8711031602_2 | _ | _ | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 1 | 0 | _ |
| 112 | 4501023080_1 | _ | _ | _ | _ | _ | 0 | 0 | _ | _ | _ | _ | _ | _ | _ | 0 | 1 | _ | _ |
| 113 | 4501025288_1 | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ | _ | _ | 0 | 0 | 1 | _ | _ |
| 114 | 4701032307_2 | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ | _ | _ | 0 | 1 | 1 | _ |
| 115 | 4701032699_1 | _ | _ | _ | _ | _ | 1 | 0 | 0 | _ | _ | _ | _ | _ | _ | 0 | 1 | 1 | _ |
| 116 | 4701034508_2 | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ | _ | _ | 0 | 1 | 1 | _ |
| 117 | 4711030178_1 | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ |
| 118 | 4711030684_1 | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ |
| 119 | 4711030700_1 | _ | _ | _ | _ | _ | _ | 1 | 1 | _ | _ | _ | _ | _ | _ | _ | 1 | 0 | _ |
| 120 | 4711036128_1 | _ | _ | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 0 | 1 | 1 | _ |
| 121 | 4901043168_1 | _ | _ | _ | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 |
| 122 | 4901045937_1 | _ | _ | _ | _ | _ | _ | 3 | 3 | 3 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 |
| 123 | 4901045937_2 | _ | _ | _ | _ | _ | _ | 3 | 3 | 3 | _ | _ | _ | _ | _ | _ | 1 | 1 | 0 |
| 124 | 4911040136_1 | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ |
| 125 | 4911041306_1 | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ |
| 126 | 4911041615_1 | _ | _ | _ | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 0 | 0 |
| 127 | 4911041692_1 | _ | _ | _ | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 |
| 128 | 4911041692_2 | _ | _ | _ | _ | _ | _ | 0 | 0 | _ | _ | _ | _ | _ | _ | _ | 1 | 1 | _ |
| 129 | 4911041719_1 | _ | _ | _ | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 |
| 130 | 4911041719_2 | _ | _ | _ | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 |
| 131 | 4911041943_1 | _ | _ | _ | _ | _ | _ | 0 | 0 | _ | _ | _ | _ | _ | _ | _ | 1 | 1 | _ |
| 132 | 4911042106_1 | _ | _ | _ | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 |
| 133 | 4911042309_3 | _ | _ | _ | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 |
| 134 | 4911042309_4 | _ | _ | _ | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 |
| 135 | 4911042339_1 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ | _ | _ | 1 | 0 | 1 |
| 136 | 4911042339_2 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ | _ | _ | 1 | 0 | 1 |
| 137 | 4911045045_1 | _ | _ | _ | _ | _ | _ | 0 | 0 | _ | _ | _ | _ | _ | _ | _ | 1 | 0 | _ |
| 138 | 8501022670_2 | _ | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 0 | 0 | 1 | _ | _ |
| 139 | 8511020905_1 | _ | _ | _ | _ | 1 | _ | 1 | _ | _ | _ | _ | _ | _ | 0 | _ | 1 | _ | _ |
| 140 | 8901042700_1 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 |
| 141 | 8901042700_2 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 |
| 142 | 8901043081_2 | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ |
| 143 | 8901043410_1 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 |
| 144 | 8901043754_2 | _ | _ | _ | _ | _ | _ | 1 | 1 | _ | _ | _ | _ | _ | _ | _ | 1 | 1 | _ |
| 145 | 8901044465_1 | _ | _ | _ | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 |
| 146 | 8911045479_1 | _ | _ | _ | _ | _ | _ | 0 | 0 | 1 | _ | _ | _ | _ | _ | _ | 1 | 1 | 0 |
| 147 | 4711031065_1 | _ | _ | _ | _ | _ | 1 | 1 | 2 | _ | _ | _ | _ | _ | _ | 0 | 0 | 1 | _ |
| 148 | 4711031473_1 | _ | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ |
| 149 | 4711031473_2 | _ | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ |
| 150 | 4901044286_1 | _ | _ | _ | _ | _ | _ | 1 | 0 | 0 | _ | _ | _ | _ | _ | _ | 0 | 1 | 1 |
| 151 | 4901045192_1 | _ | _ | _ | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 0 | 1 | 1 |
| 152 | 4901045871_2 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ | _ | _ | 0 | 1 | 0 |

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| | | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 |
| 153 | 4911042073_2 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ | _ | _ | 0 | 1 | 0 |
| 154 | 4911042412_1 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ | _ | _ | 0 | 1 | 1 |
| 155 | 5101054861_2 | _ | _ | _ | _ | _ | _ | _ | 1 | 1 | _ | _ | _ | _ | _ | _ | _ | 1 | 1 |
| 156 | 5101055253_1 | _ | _ | _ | _ | _ | _ | _ | 0 | 0 | _ | _ | _ | _ | _ | _ | _ | 1 | 1 |
| 157 | 5101055253_2 | _ | _ | _ | _ | _ | _ | _ | 0 | 0 | _ | _ | _ | _ | _ | _ | _ | 1 | 1 |
| 158 | 5101055420_2 | _ | _ | _ | _ | _ | _ | _ | 1 | 1 | _ | _ | _ | _ | _ | _ | _ | 1 | 0 |
| 159 | 5111050717_1 | _ | _ | _ | _ | _ | _ | _ | 0 | 0 | _ | _ | _ | _ | _ | _ | _ | 1 | 1 |
| 160 | 5111050876_1 | _ | _ | _ | _ | _ | _ | _ | 1 | 1 | _ | _ | _ | _ | _ | _ | _ | 1 | 0 |
| 161 | 5111050957_1 | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ |
| 162 | 5111051164_1 | _ | _ | _ | _ | _ | _ | _ | 0 | 0 | _ | _ | _ | _ | _ | _ | _ | 1 | 1 |
| 163 | 5111051173_1 | _ | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ |
| 164 | 5111051173_2 | _ | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ |
| 165 | 5111051627_1 | _ | _ | _ | _ | _ | _ | _ | 1 | 1 | _ | _ | _ | _ | _ | _ | _ | 1 | 1 |
| 166 | 5111051785_2 | _ | _ | _ | _ | _ | _ | _ | 1 | 1 | _ | _ | _ | _ | _ | _ | _ | 1 | 0 |
| 167 | 5111051856_1 | _ | _ | _ | _ | _ | _ | _ | 0 | 0 | _ | _ | _ | _ | _ | _ | _ | 1 | 1 |
| 168 | 5111052069_2 | _ | _ | _ | _ | _ | _ | _ | 1 | 1 | _ | _ | _ | _ | _ | _ | _ | 1 | 0 |
| 169 | 5111052272_1 | _ | _ | _ | _ | _ | _ | _ | 2 | 2 | _ | _ | _ | _ | _ | _ | _ | 1 | 0 |
| 170 | 5111052498_1 | _ | _ | _ | _ | _ | _ | _ | 1 | 1 | _ | _ | _ | _ | _ | _ | _ | 1 | 0 |
| 171 | 5111052498_2 | _ | _ | _ | _ | _ | _ | _ | 1 | 1 | _ | _ | _ | _ | _ | _ | _ | 1 | 0 |
| 172 | 8901043742_2 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ | _ | _ | 0 | 1 | 1 |
| 173 | 8901044465_2 | _ | _ | _ | _ | _ | _ | 0 | 0 | 0 | _ | _ | _ | _ | _ | _ | 0 | 1 | 0 |
| 174 | 8911042116_1 | _ | _ | _ | _ | _ | _ | 1 | 1 | 1 | _ | _ | _ | _ | _ | _ | 0 | 1 | 0 |
| 175 | 9101052988_1 | _ | _ | _ | _ | _ | _ | _ | 0 | 0 | _ | _ | _ | _ | _ | _ | _ | 1 | 1 |
| 176 | 9111050780_1 | _ | _ | _ | _ | _ | _ | _ | 0 | 0 | _ | _ | _ | _ | _ | _ | _ | 1 | 1 |
| 177 | 9111051257_1 | _ | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ |
| 178 | 9111051946_1 | _ | _ | _ | _ | _ | _ | _ | 0 | 0 | _ | _ | _ | _ | _ | _ | _ | 1 | 1 |
| 179 | 9111052219_1 | _ | _ | _ | _ | _ | _ | _ | 0 | 0 | _ | _ | _ | _ | _ | _ | _ | 1 | 1 |
| 180 | 4901044677_1 | _ | _ | _ | _ | _ | _ | 2 | 2 | 2 | _ | _ | _ | _ | _ | _ | 0 | 0 | 1 |
| 181 | 4911041969_1 | _ | _ | _ | _ | _ | _ | 2 | _ | 2 | _ | _ | _ | _ | _ | _ | 0 | _ | 1 |
| 182 | 5101052936_1 | _ | _ | _ | _ | _ | _ | _ | 0 | 0 | _ | _ | _ | _ | _ | _ | _ | 0 | 1 |
| 183 | 5111050424_1 | _ | _ | _ | _ | _ | _ | _ | 0 | 0 | _ | _ | _ | _ | _ | _ | _ | 0 | 1 |
| 184 | 5111051130_1 | _ | _ | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 185 | 5111052386_1 | _ | _ | _ | _ | _ | _ | _ | 2 | 2 | _ | _ | _ | _ | _ | _ | _ | 0 | 1 |
| 186 | 5301062472_1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 187 | 5301062472_2 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 188 | 5301062747_1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 189 | 5301062747_2 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 190 | 5301062898_1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 191 | 5301062970_1 | _ | _ | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 192 | 5301062970_2 | _ | _ | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 193 | 5301063350_1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 194 | 5301063356_1 | _ | _ | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |

| # | ID_der | PKWHH | | | | | | | | | PKWCS | | | | | | | | |
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| | | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 |
| 195 | 5301063519_1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 196 | 5301063613_2 | _ | _ | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 197 | 5301063907_1 | _ | _ | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 198 | 5301063907_2 | _ | _ | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 199 | 5301063963_1 | _ | _ | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 200 | 5301064541_1 | _ | _ | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 201 | 5301064818_1 | _ | _ | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 202 | 5301064818_2 | _ | _ | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 203 | 5301066167_1 | _ | _ | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 204 | 5311060121_2 | _ | _ | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 205 | 5311060122_1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 206 | 5311060313_2 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 207 | 5311060382_1 | _ | _ | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 208 | 5311060382_2 | _ | _ | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 209 | 5311060622_1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 210 | 5311060625_1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 211 | 5311061003_1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 212 | 5311061026_1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 213 | 5311061529_1 | _ | _ | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 214 | 5311061573_1 | _ | _ | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 215 | 5311061573_2 | _ | _ | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 216 | 5311061658_1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 217 | 5311061727_1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 218 | 5311061840_1 | _ | _ | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 219 | 5311062501_1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 220 | 5311062501_2 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 221 | 5311062637_1 | _ | _ | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 222 | 5311062637_2 | _ | _ | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 223 | 9101052988_2 | _ | _ | _ | _ | _ | _ | _ | 0 | 0 | _ | _ | _ | _ | _ | _ | _ | 0 | 1 |
| 224 | 9111050972_1 | _ | _ | _ | _ | _ | _ | _ | 0 | 0 | _ | _ | _ | _ | _ | _ | _ | 0 | 1 |
| 225 | 9301062723_1 | _ | _ | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 226 | 9301063524_1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 227 | 9301064023_2 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 228 | 9301064235_1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 229 | 9301064761_1 | _ | _ | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 230 | 9311061386_1 | _ | _ | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 231 | 9311062410_1 | _ | _ | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 232 | 9311062410_2 | _ | _ | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |
| 233 | 9311062590_2 | _ | _ | _ | _ | _ | _ | _ | _ | 0 | _ | _ | _ | _ | _ | _ | _ | _ | 1 |

# Appendix B
# R scripts for the matching method

## First step: Import csv files
# The prepared input files of each year were imported to R separately.
```
O12 <- read.csv("T&preC2012.csv", header = TRUE, sep = ";")
O13 <- read.csv("T&preC2013.csv", header = TRUE, sep = ";")
O14 <- read.csv("T&preC2014.csv", header = TRUE, sep = ";")
O15 <- read.csv("T&preC2015.csv", header = TRUE, sep = ";")
O16 <- read.csv("T&preC2016.csv", header = TRUE, sep = ";")
O17 <- read.csv("T&preC2017.csv", header = TRUE, sep = ";")
O18 <- read.csv("T&preC2018.csv", header = TRUE, sep = ";")
O19 <- read.csv("T&preC2019.csv", header = TRUE, sep = ";")
O20 <- read.csv("T&preC2020.csv", header = TRUE, sep = ";")
```

## Second step: Check the structure of the input data and define if numerical or categorical.
# The meaning of the value corresponding to each covariate must have been recognized.
```
str(O12)
str(O13)
str(O14)
str(O15)
str(O16)
str(O17)
str(O18)
str(O19)
str(O20)
```

# Data types were modified, since both numerical and categorical data can take numerical values #and by default, R recognizes all the numbers as integers which were wrong in this study due to #the presence of many categorical data. Especially, defining correct data type is crucial for R in the #matching procedure.

```
#2012
O12$RAUMTYP<- as.factor(O12$RAUMTYP)
O12$EINKO <- as.factor(O12$EINKO)
O12$SEX <- as.factor(O12$SEX)
O12$ALTER <- as.factor(O12$ALTER)
O12$SCHULAB <- as.factor(O12$SCHULAB)
O12$BERUF <- as.factor(O12$BERUF)
O12$FSPKW <- as.factor(O12$FSPKW)
O12$P.T.card <- as.factor(O12$P.T.card)
O12$Treat <- as.factor(O12$Treat)

#2013
O13$RAUMTYP<- as.factor(O13$RAUMTYP)
O13$EINKO <- as.factor(O13$EINKO)
O13$SEX <- as.factor(O13$SEX)
O13$ALTER <- as.factor(O13$ALTER)
O13$SCHULAB <- as.factor(O13$SCHULAB)
O13$BERUF <- as.factor(O13$BERUF)
O13$FSPKW <- as.factor(O13$FSPKW)
O13$P.T.card <- as.factor(O13$P.T.card)
O13$Treat <- as.factor(O13$Treat)

#2014
O14$RAUMTYP<- as.factor(O14$RAUMTYP)
O14$EINKO <- as.factor(O14$EINKO)
O14$SEX <- as.factor(O14$SEX)
O14$ALTER <- as.factor(O14$ALTER)
O14$SCHULAB <- as.factor(O14$SCHULAB)
O14$BERUF <- as.factor(O14$BERUF)
O14$FSPKW <- as.factor(O14$FSPKW)
O14$P.T.card <- as.factor(O14$P.T.card)
O14$Treat <- as.factor(O14$Treat)

#2015
O15$RAUMTYP<- as.factor(O15$RAUMTYP)
O15$EINKO <- as.factor(O15$EINKO)
O15$SEX <- as.factor(O15$SEX)
O15$ALTER <- as.factor(O15$ALTER)
O15$SCHULAB <- as.factor(O15$SCHULAB)
O15$BERUF <- as.factor(O15$BERUF)
O15$FSPKW <- as.factor(O15$FSPKW)
O15$P.T.card <- as.factor(O15$P.T.card)
O15$Treat <- as.factor(O15$Treat)

#2016
O16$RAUMTYP<- as.factor(O16$RAUMTYP)
```

```
O16$EINKO <- as.factor(O16$EINKO)
O16$SEX <- as.factor(O16$SEX)
O16$ALTER <- as.factor(O16$ALTER)
O16$SCHULAB <- as.factor(O16$SCHULAB)
O16$BERUF <- as.factor(O16$BERUF)
O16$FSPKW <- as.factor(O16$FSPKW)
O16$P.T.card <- as.factor(O16$P.T.card)
O16$Treat <- as.factor(O16$Treat)

#2017
O17$RAUMTYP<- as.factor(O17$RAUMTYP)
O17$EINKO <- as.factor(O17$EINKO)
O17$SEX <- as.factor(O17$SEX)
O17$ALTER <- as.factor(O17$ALTER)
O17$SCHULAB <- as.factor(O17$SCHULAB)
O17$BERUF <- as.factor(O17$BERUF)
O17$FSPKW <- as.factor(O17$FSPKW)
O17$P.T.card <- as.factor(O17$P.T.card)
O17$Treat <- as.factor(O17$Treat)

#2018
O18$RAUMTYP<- as.factor(O18$RAUMTYP)
O18$EINKO <- as.factor(O18$EINKO)
O18$SEX <- as.factor(O18$SEX)
O18$ALTER <- as.factor(O18$ALTER)
O18$SCHULAB <- as.factor(O18$SCHULAB)
O18$BERUF <- as.factor(O18$BERUF)
O18$FSPKW <- as.factor(O18$FSPKW)
O18$P.T.card <- as.factor(O18$P.T.card)
O18$Treat <- as.factor(O18$Treat)

#2019
O19$RAUMTYP<- as.factor(O19$RAUMTYP)
O19$EINKO <- as.factor(O19$EINKO)
O19$SEX <- as.factor(O19$SEX)
O19$ALTER <- as.factor(O19$ALTER)
O19$SCHULAB <- as.factor(O19$SCHULAB)
O19$BERUF <- as.factor(O19$BERUF)
O19$FSPKW <- as.factor(O19$FSPKW)
O19$P.T.card <- as.factor(O19$P.T.card)
O19$Treat <- as.factor(O19$Treat)

#2020
O20$RAUMTYP<- as.factor(O20$RAUMTYP)
O20$EINKO <- as.factor(O20$EINKO)
O20$SEX <- as.factor(O20$SEX)
O20$ALTER <- as.factor(O20$ALTER)
O20$SCHULAB <- as.factor(O20$SCHULAB)
O20$BERUF <- as.factor(O20$BERUF)
O20$FSPKW <- as.factor(O20$FSPKW)
O20$P.T.card <- as.factor(O20$P.T.card)
O20$Treat <- as.factor(O20$Treat)

########## START MATCHING
```

# The basic idea of matching method is to compare units that have the same values of the #covariates, but different values of the treatment. To do so, we first construct the treated unit and #then find the non-treated unit that has very similar covariates values.

## Third step: Load the MatchIT package
#R packages are extensions to the R statistical programming language. A package is a collection #of code, data, and documentation that users of R can install.

```
library(MatchIt)
```

## Forth step: Run the Nearest Neighbour Method, Ratio 5
# In summary, the method was the neatest neighbor matching without replacement, the #"distance" was propensity score estimated with logistic regression, and the target estimand (the #purpose of the statistical analysis) was ATT. Indeed, ATT means average treatment effect on #the treated when the outcome of treated are observed and controls are missing, like this study. #The ratio of this method was set at 5, meaning that for each treated unit, there should be five matched IDs.

```
#2012
Near5_12 <- matchit(Treat ~ RAUMTYP + HHGRO + P0_10 + EINKO + PKWHH + SEX + ALTER +
SCHULAB + BERUF + FSPKW + P.T.card, data = O12, method = "Nearest", ratio = 5)
```

```
Near5_12
summary(Near5_12)

#2013
Near5_13 <- matchit(Treat ~ RAUMTYP + HHGRO + P0_10 + EINKO + PKWHH + SEX + ALTER +
SCHULAB + BERUF + FSPKW + P.T.card, data = O13, method = "Nearest", ratio = 5)
Near5_13
summary(Near5_13)

#2014
Near5_14 <- matchit(Treat ~ RAUMTYP + HHGRO + P0_10 + EINKO + PKWHH + SEX + ALTER +
SCHULAB + BERUF + FSPKW + P.T.card, data = O14, method = "Nearest", ratio = 5)
Near5_14
summary(Near5_14)

#2015
Near5_15 <- matchit(Treat ~ RAUMTYP + HHGRO + P0_10 + EINKO + PKWHH + SEX + ALTER +
SCHULAB + BERUF + FSPKW + P.T.card, data = O15, method = "Nearest", ratio = 5)
Near5_15
summary(Near5_15)

#2016
Near5_16 <- matchit(Treat ~ RAUMTYP + HHGRO + P0_10 + EINKO + PKWHH + SEX + ALTER +
SCHULAB + BERUF + FSPKW + P.T.card, data = O16, method = "Nearest", ratio = 5)
Near5_16
summary(Near5_16)

#2017
Near5_17 <- matchit(Treat ~ RAUMTYP + HHGRO + P0_10 + EINKO + PKWHH + SEX + ALTER +
SCHULAB + BERUF + FSPKW + P.T.card, data = O17, method = "Nearest", ratio = 5)
Near5_17
summary(Near5_17)

#2018
Near5_18 <- matchit(Treat ~ RAUMTYP + HHGRO + P0_10 + EINKO + PKWHH + SEX + ALTER +
SCHULAB + BERUF + FSPKW + P.T.card, data = O18, method = "Nearest", ratio = 5)
Near5_18
summary(Near5_18)

#2019
Near5_19 <- matchit(Treat ~ RAUMTYP + HHGRO + P0_10 + EINKO + PKWHH + SEX + ALTER +
SCHULAB + BERUF + FSPKW + P.T.card, data = O19, method = "Nearest", ratio = 5)
Near5_19
summary(Near5_19)

#2020
Near5_20 <- matchit(Treat ~ RAUMTYP + HHGRO + P0_10 + EINKO + PKWHH + SEX + ALTER +
SCHULAB + BERUF + FSPKW + P.T.card, data = O20, method = "Nearest", ratio = 5)
Near5_20
summary(Near5_20)
```

#Fifth step: Save the output files

#The saved output files look like **Table 5.8** in which "distance" column corresponds the #propensity score.

```
#2012
Save_12 = match.data(Near5_12)
names(Save_12)
head(Save_12)
write.csv(Save_12 , file = "Matched_N5_12.csv")

#2013
Save_13 = match.data(Near5_13)
names(Save_13)
head(Save_13)
write.csv(Save_13, file = "Matched_N5_13.csv")

#2014
Save_14 = match.data(Near5_14)
names(Save_14)
head(Save_14)
write.csv(Save_14, file = "Matched_N5_14.csv")

#2015
Save_15 = match.data(Near5_15)
names(Save_15)
head(Save_15)
write.csv(Save_15, file = "Matched_N5_15.csv")

#2016
Save_16 = match.data(Near5_16)
names(Save_16)
head(Save_16)
write.csv(Save_16, file = "Matched_N5_16.csv")

#2017
Save_17 = match.data(Near5_173)
names(Save_17)
head(Save_17)
write.csv(Save_17, file = "Matched_N5_17.csv")

#2018
Save_18 = match.data(Near5_18)
names(Save_18)
head(Save_18)
write.csv(Save_18 , file = "Matched_N5_18.csv")

#2019
Save_19 = match.data(Near5_19)
names(Save_19)
```

```
head(Save_19)
write.csv(Save_19 , file = "Matched_N5_19.csv")

#2020
Save_20 = match.data(Near5_20)
names(Save_20)
head(Save_20)
write.csv(Save_20 , file = "Matched_N5_20.csv")
```

# Appendix C
# Tables of information for assessing balance

Three main information tables are displayed when “summary()” is called on a Matchit object. The balance statistics for each covariate before matching, the balance statistics after matching, and the percent reduction in imbalance are included. All the explanations of attributes in each table were detailed in **Section 5.1.2.1**.

**Table A. C–1**
Summary of balance for all data (2012)

| Covariate | Means Treated | Means Control | Std. Mean Diff | Var. Ratio | eCDF Mean | eCDF Max |
|---|---|---|---|---|---|---|
| distance | 1,000 | 0,000 | 8067037,007 | 67,998 | 0,909 | 1,000 |
| RAUMTYP1 | 0,800 | 0,447 | 0,882 | , | 0,353 | 0,353 |
| RAUMTYP2 | 0,200 | 0,235 | -0,087 | , | 0,035 | 0,035 |
| RAUMTYP3 | 0,000 | 0,205 | -0,510 | , | 0,205 | 0,205 |
| RAUMTYP4 | 0,000 | 0,091 | -0,317 | , | 0,091 | 0,091 |
| RAUMTYP5 | 0,000 | 0,022 | -0,151 | , | 0,022 | 0,022 |
| HHGRO | 1,600 | 2,314 | -0,799 | 0,637 | 0,102 | 0,347 |
| P0_10 | 0,400 | 0,190 | 0,234 | 2,780 | 0,055 | 0,145 |
| EINKO1 | 0,000 | 0,004 | -0,061 | , | 0,004 | 0,004 |
| EINKO2 | 0,000 | 0,031 | -0,181 | , | 0,031 | 0,031 |
| EINKO3 | 0,200 | 0,102 | 0,246 | , | 0,098 | 0,098 |
| EINKO4 | 0,200 | 0,118 | 0,204 | , | 0,082 | 0,082 |
| EINKO5 | 0,200 | 0,144 | 0,140 | , | 0,056 | 0,056 |
| EINKO6 | 0,200 | 0,139 | 0,153 | , | 0,061 | 0,061 |
| EINKO7 | 0,000 | 0,141 | -0,406 | , | 0,141 | 0,141 |
| EINKO8 | 0,200 | 0,322 | -0,304 | , | 0,122 | 0,122 |
| PKWHH | 0,400 | 1,399 | -1,824 | 0,523 | 0,200 | 0,526 |
| SEX1 | 0,600 | 0,499 | 0,206 | , | 0,101 | 0,101 |
| SEX2 | 0,400 | 0,501 | -0,206 | , | 0,101 | 0,101 |
| ALTER1 | 0,000 | 0,004 | -0,061 | , | 0,004 | 0,004 |
| ALTER2 | 0,000 | 0,022 | -0,151 | , | 0,022 | 0,022 |
| ALTER3 | 0,000 | 0,061 | -0,256 | , | 0,061 | 0,061 |
| ALTER4 | 0,600 | 0,255 | 0,704 | , | 0,345 | 0,345 |
| ALTER5 | 0,400 | 0,261 | 0,285 | , | 0,139 | 0,139 |
| ALTER6 | 0,000 | 0,233 | -0,553 | , | 0,233 | 0,233 |
| ALTER7 | 0,000 | 0,165 | -0,445 | , | 0,165 | 0,165 |
| SCHULAB1 | 0,000 | 0,514 | -1,028 | , | 0,514 | 0,514 |
| SCHULAB2 | 1,000 | 0,482 | 1,036 | , | 0,518 | 0,518 |
| SCHULAB3 | 0,000 | 0,004 | -0,061 | , | 0,004 | 0,004 |
| BERUF1 | 0,800 | 0,355 | 1,113 | , | 0,445 | 0,445 |
| BERUF2 | 0,200 | 0,242 | -0,105 | , | 0,042 | 0,042 |
| BERUF3 | 0,000 | 0,035 | -0,192 | , | 0,035 | 0,035 |
| BERUF4 | 0,000 | 0,368 | -0,764 | , | 0,368 | 0,368 |
| FSPKW0 | 0,000 | 0,022 | -0,151 | , | 0,022 | 0,022 |

| | | | | | | |
|---|---|---|---|---|---|---|
| FSPKW1 | 1,000 | 0,978 | 0,151 | , | 0,022 | 0,022 |
| P,T,card0 | 0,000 | 0,756 | -1,744 | , | 0,756 | 0,756 |
| P,T,card1 | 1,000 | 0,244 | 1,744 | , | 0,756 | 0,756 |

**Table A. C–2**
Summary of balance for matched data (2012)

| Covariate | Means Treated | Means Control | Std. Mean Diff | Var. Ratio | eCDF Mean | eCDF Max | Std. Pair Dist. |
|---|---|---|---|---|---|---|---|
| distance | 1,000 | 0,000 | 8067036,712 | 4,241 | 0,463 | 1,000 | 8067036,712 |
| RAUMTYP1 | 0,800 | 0,520 | 0,700 | , | 0,280 | 0,280 | 1,100 |
| RAUMTYP2 | 0,200 | 0,280 | -0,200 | , | 0,080 | 0,080 | 1,000 |
| RAUMTYP3 | 0,000 | 0,080 | -0,199 | , | 0,080 | 0,080 | 0,199 |
| RAUMTYP4 | 0,000 | 0,040 | -0,140 | , | 0,040 | 0,040 | 0,140 |
| RAUMTYP5 | 0,000 | 0,080 | -0,546 | , | 0,080 | 0,080 | 0,546 |
| HHGRO | 1,600 | 2,160 | -0,626 | 0,514 | 0,080 | 0,200 | 1,521 |
| P0_10 | 0,400 | 0,280 | 0,134 | 1,739 | 0,030 | 0,080 | 0,581 |
| EINKO1 | 0,000 | 0,040 | -0,662 | , | 0,040 | 0,040 | 0,662 |
| EINKO2 | 0,000 | 0,040 | -0,230 | , | 0,040 | 0,040 | 0,230 |
| EINKO3 | 0,200 | 0,000 | 0,500 | , | 0,200 | 0,200 | 0,500 |
| EINKO4 | 0,200 | 0,160 | 0,100 | , | 0,040 | 0,040 | 0,700 |
| EINKO5 | 0,200 | 0,200 | 0,000 | , | 0,000 | 0,000 | 0,320 |
| EINKO6 | 0,200 | 0,080 | 0,300 | , | 0,120 | 0,120 | 0,300 |
| EINKO7 | 0,000 | 0,040 | -0,116 | , | 0,040 | 0,040 | 0,116 |
| EINKO8 | 0,200 | 0,440 | -0,600 | , | 0,240 | 0,240 | 1,400 |
| PKWHH | 0,400 | 0,640 | -0,438 | 0,738 | 0,048 | 0,160 | 0,876 |
| SEX1 | 0,600 | 0,640 | -0,082 | , | 0,040 | 0,040 | 1,061 |
| SEX2 | 0,400 | 0,360 | 0,082 | , | 0,040 | 0,040 | 1,061 |
| ALTER1 | 0,000 | 0,040 | -0,662 | , | 0,040 | 0,040 | 0,662 |
| ALTER2 | 0,000 | 0,080 | -0,546 | , | 0,080 | 0,080 | 0,546 |
| ALTER3 | 0,000 | 0,120 | -0,504 | , | 0,120 | 0,120 | 0,504 |
| ALTER4 | 0,600 | 0,240 | 0,735 | , | 0,360 | 0,360 | 1,225 |
| ALTER5 | 0,400 | 0,280 | 0,245 | , | 0,120 | 0,120 | 1,388 |
| ALTER6 | 0,000 | 0,160 | -0,380 | , | 0,160 | 0,160 | 0,380 |
| ALTER7 | 0,000 | 0,080 | -0,217 | , | 0,080 | 0,080 | 0,217 |
| SCHULAB1 | 0,000 | 0,160 | -0,320 | , | 0,160 | 0,160 | 0,320 |
| SCHULAB2 | 1,000 | 0,800 | 0,400 | , | 0,200 | 0,200 | 0,400 |
| SCHULAB3 | 0,000 | 0,040 | -0,662 | , | 0,040 | 0,040 | 0,662 |
| BERUF1 | 0,800 | 0,440 | 0,900 | , | 0,360 | 0,360 | 1,100 |
| BERUF2 | 0,200 | 0,200 | 0,000 | , | 0,000 | 0,000 | 0,240 |
| BERUF3 | 0,000 | 0,200 | -1,091 | , | 0,200 | 0,200 | 1,091 |
| BERUF4 | 0,000 | 0,160 | -0,332 | , | 0,160 | 0,160 | 0,332 |
| FSPKW0 | 0,000 | 0,080 | -0,546 | , | 0,080 | 0,080 | 0,546 |
| FSPKW1 | 1,000 | 0,920 | 0,546 | , | 0,080 | 0,080 | 0,546 |
| P,T,card0 | 0,000 | 0,080 | -0,185 | , | 0,080 | 0,080 | 0,185 |
| P,T,card1 | 1,000 | 0,920 | 0,185 | , | 0,080 | 0,080 | 0,185 |

**Table A. C–3**
Percent balance improvement (2012)

| Covariate | Std. Mean Diff | Var. Ratio | eCDF Mean | eCDF Max |
|---|---|---|---|---|
| distance | 0 | 65,8 | 49,1 | 0 |
| RAUMTYP1 | 20,6 | , | 20,6 | 20,6 |
| RAUMTYP2 | -130,2 | , | -130,2 | -130,2 |
| RAUMTYP3 | 61 | , | 61 | 61 |
| RAUMTYP4 | 55,8 | , | 55,8 | 55,8 |
| RAUMTYP5 | -260,7 | , | -260,7 | -260,7 |
| HHGRO | 21,6 | -47,4 | 21,6 | 42,3 |
| P0_10 | 42,8 | 45,9 | 45,6 | 44,7 |
| EINKO1 | -982 | , | -982 | -982 |
| EINKO2 | -27,3 | , | -27,3 | -27,3 |
| EINKO3 | -103,4 | , | -103,4 | -103,4 |
| EINKO4 | 51 | , | 51 | 51 |
| EINKO5 | 100 | , | 100 | 100 |
| EINKO6 | -95,5 | , | -95,5 | -95,5 |
| EINKO7 | 71,5 | , | 71,5 | 71,5 |
| EINKO8 | -97,3 | , | -97,3 | -97,3 |
| PKWHH | 76 | 53,1 | 76 | 69,6 |
| SEX1 | 60,4 | , | 60,4 | 60,4 |
| SEX2 | 60,4 | , | 60,4 | 60,4 |
| ALTER1 | -982 | , | -982 | -982 |
| ALTER2 | -260,7 | , | -260,7 | -260,7 |
| ALTER3 | -96,7 | , | -96,7 | -96,7 |
| ALTER4 | -4,4 | , | -4,4 | -4,4 |
| ALTER5 | 13,9 | , | 13,9 | 13,9 |
| ALTER6 | 31,3 | , | 31,3 | 31,3 |
| ALTER7 | 51,4 | , | 51,4 | 51,4 |
| SCHULAB1 | 68,9 | , | 68,9 | 68,9 |
| SCHULAB2 | 61,4 | , | 61,4 | 61,4 |
| SCHULAB3 | -982 | , | -982 | -982 |
| BERUF1 | 19,1 | , | 19,1 | 19,1 |
| BERUF2 | 100 | , | 100 | 100 |
| BERUF3 | -469,5 | , | -469,5 | -469,5 |
| BERUF4 | 56,5 | , | 56,5 | 56,5 |
| FSPKW0 | -260,7 | , | -260,7 | -260,7 |
| FSPKW1 | -260,7 | , | -260,7 | -260,7 |
| P,T,card0 | 89,4 | , | 89,4 | 89,4 |
| P,T,card1 | 89,4 | , | 89,4 | 89,4 |

**Table A. C–4**

Summary of balance for all data (2013)

| Covariate | Means Treated | Means Control | Std. Mean Diff | Var. Ratio | eCDF Mean | eCDF Max |
|---|---|---|---|---|---|---|
| distance | 0,398 | 0,008 | 1,299 | 67,126 | 0,648 | 0,861 |
| RAUMTYP1 | 0,917 | 0,450 | 1,690 | , | 0,467 | 0,467 |
| RAUMTYP2 | 0,083 | 0,240 | -0,568 | , | 0,157 | 0,157 |
| RAUMTYP3 | 0,000 | 0,205 | -0,510 | , | 0,205 | 0,205 |
| RAUMTYP4 | 0,000 | 0,074 | -0,284 | , | 0,074 | 0,074 |
| RAUMTYP5 | 0,000 | 0,031 | -0,180 | , | 0,031 | 0,031 |
| HHGRO | 1,583 | 2,270 | -1,028 | 0,373 | 0,098 | 0,254 |
| P0_10 | 0,167 | 0,186 | -0,033 | 1,218 | 0,021 | 0,047 |
| EINKO1 | 0,000 | 0,006 | -0,081 | , | 0,006 | 0,006 |
| EINKO2 | 0,000 | 0,032 | -0,184 | , | 0,032 | 0,032 |
| EINKO3 | 0,250 | 0,075 | 0,404 | , | 0,175 | 0,175 |
| EINKO4 | 0,167 | 0,138 | 0,076 | , | 0,028 | 0,028 |
| EINKO5 | 0,083 | 0,136 | -0,192 | , | 0,053 | 0,053 |
| EINKO6 | 0,167 | 0,126 | 0,110 | , | 0,041 | 0,041 |
| EINKO7 | 0,083 | 0,136 | -0,192 | , | 0,053 | 0,053 |
| EINKO8 | 0,000 | 0,103 | -0,341 | , | 0,103 | 0,103 |
| EINKO9 | 0,167 | 0,119 | 0,128 | , | 0,048 | 0,048 |
| EINKO10 | 0,083 | 0,128 | -0,161 | , | 0,044 | 0,044 |
| PKWHH | 0,250 | 1,411 | -2,567 | 0,316 | 0,166 | 0,661 |
| SEX1 | 0,583 | 0,516 | 0,136 | , | 0,067 | 0,067 |
| SEX2 | 0,417 | 0,484 | -0,136 | , | 0,067 | 0,067 |
| ALTER1 | 0,000 | 0,003 | -0,057 | , | 0,003 | 0,003 |
| ALTER2 | 0,083 | 0,032 | 0,185 | , | 0,051 | 0,051 |
| ALTER3 | 0,250 | 0,089 | 0,372 | , | 0,161 | 0,161 |
| ALTER4 | 0,250 | 0,285 | -0,082 | , | 0,035 | 0,035 |
| ALTER5 | 0,417 | 0,258 | 0,323 | , | 0,159 | 0,159 |
| ALTER6 | 0,000 | 0,200 | -0,502 | , | 0,200 | 0,200 |
| ALTER7 | 0,000 | 0,133 | -0,394 | , | 0,133 | 0,133 |
| SCHULAB1 | 0,333 | 0,500 | -0,354 | , | 0,167 | 0,167 |
| SCHULAB2 | 0,667 | 0,495 | 0,365 | , | 0,172 | 0,172 |
| SCHULAB3 | 0,000 | 0,005 | -0,074 | , | 0,005 | 0,005 |
| BERUF1 | 0,750 | 0,428 | 0,743 | , | 0,322 | 0,322 |
| BERUF2 | 0,083 | 0,232 | -0,537 | , | 0,148 | 0,148 |
| BERUF3 | 0,167 | 0,039 | 0,344 | , | 0,128 | 0,128 |
| BERUF4 | 0,000 | 0,302 | -0,659 | , | 0,302 | 0,302 |
| FSPKW0 | 0,000 | 0,040 | -0,205 | , | 0,040 | 0,040 |
| FSPKW1 | 1,000 | 0,960 | 0,205 | , | 0,040 | 0,040 |
| P,T,card0 | 0,083 | 0,743 | -2,385 | , | 0,659 | 0,659 |
| P,T,card1 | 0,917 | 0,258 | 2,385 | , | 0,659 | 0,659 |

**Table A. C–5**

Summary of balance for matched data (2013)

| Covariate | Means Treated | Means Control | Std. Mean Diff | Var. Ratio | eCDF Mean | eCDF Max | Std. Pair Dist. |
|---|---|---|---|---|---|---|---|
| distance | 0,398 | 0,109 | 0,963 | 9,041 | 0,035 | 0,650 | 0,963 |
| RAUMTYP1 | 0,917 | 0,833 | 0,302 | , | 0,083 | 0,083 | 0,905 |
| RAUMTYP2 | 0,083 | 0,167 | -0,302 | , | 0,083 | 0,083 | 0,905 |
| RAUMTYP3 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| RAUMTYP4 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| RAUMTYP5 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| HHGRO | 1,583 | 1,817 | -0,349 | 0,517 | 0,033 | 0,100 | 1,197 |
| P0_10 | 0,167 | 0,250 | -0,144 | 0,926 | 0,021 | 0,083 | 0,549 |
| EINKO1 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| EINKO2 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| EINKO3 | 0,250 | 0,150 | 0,231 | , | 0,100 | 0,100 | 0,693 |
| EINKO4 | 0,167 | 0,183 | -0,045 | , | 0,017 | 0,017 | 0,671 |
| EINKO5 | 0,083 | 0,117 | -0,121 | , | 0,033 | 0,033 | 0,724 |
| EINKO6 | 0,167 | 0,217 | -0,134 | , | 0,050 | 0,050 | 0,671 |
| EINKO7 | 0,083 | 0,117 | -0,121 | , | 0,033 | 0,033 | 0,724 |
| EINKO8 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| EINKO9 | 0,167 | 0,100 | 0,179 | , | 0,067 | 0,067 | 0,716 |
| EINKO10 | 0,083 | 0,117 | -0,121 | , | 0,033 | 0,033 | 0,603 |
| PKWHH | 0,250 | 0,650 | -0,884 | 0,614 | 0,057 | 0,350 | 1,106 |
| SEX1 | 0,583 | 0,550 | 0,068 | , | 0,033 | 0,033 | 0,676 |
| SEX2 | 0,417 | 0,450 | -0,068 | , | 0,033 | 0,033 | 0,676 |
| ALTER1 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| ALTER2 | 0,083 | 0,050 | 0,121 | , | 0,033 | 0,033 | 0,362 |
| ALTER3 | 0,250 | 0,300 | -0,116 | , | 0,050 | 0,050 | 0,962 |
| ALTER4 | 0,250 | 0,233 | 0,039 | , | 0,017 | 0,017 | 0,808 |
| ALTER5 | 0,417 | 0,417 | 0,000 | , | 0,000 | 0,000 | 0,533 |
| ALTER6 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| ALTER7 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| SCHULAB1 | 0,333 | 0,400 | -0,141 | , | 0,067 | 0,067 | 0,990 |
| SCHULAB2 | 0,667 | 0,600 | 0,141 | , | 0,067 | 0,067 | 0,990 |
| SCHULAB3 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| BERUF1 | 0,750 | 0,767 | -0,039 | , | 0,017 | 0,017 | 0,731 |
| BERUF2 | 0,083 | 0,133 | -0,181 | , | 0,050 | 0,050 | 0,543 |
| BERUF3 | 0,167 | 0,100 | 0,179 | , | 0,067 | 0,067 | 0,626 |
| BERUF4 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| FSPKW0 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| FSPKW1 | 1,000 | 1,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| P,T,card0 | 0,083 | 0,267 | -0,663 | , | 0,183 | 0,183 | 0,663 |
| P,T,card1 | 0,917 | 0,733 | 0,663 | , | 0,183 | 0,183 | 0,663 |

**Table A. C–6**
Percent balance improvement (2013)

| Covariate | Std. Mean Diff | Var. Ratio | eCDF Mean | eCDF Max |
|---|---|---|---|---|
| distance | 25,9 | 47,7 | 94,6 | 24,5 |
| RAUMTYP1 | 82,2 | , | 82,2 | 82,2 |
| RAUMTYP2 | 46,9 | , | 46,9 | 46,9 |
| RAUMTYP3 | 100 | , | 100 | 100 |
| RAUMTYP4 | 100 | , | 100 | 100 |
| RAUMTYP5 | 100 | , | 100 | 100 |
| HHGRO | 66 | 33,2 | 66 | 60,7 |
| P0_10 | -339,6 | 60,7 | 1,7 | -79,2 |
| EINKO1 | 100 | , | 100 | 100 |
| EINKO2 | 100 | , | 100 | 100 |
| EINKO3 | 42,8 | , | 42,8 | 42,8 |
| EINKO4 | 41 | , | 41 | 41 |
| EINKO5 | 37 | , | 37 | 37 |
| EINKO6 | -21,6 | , | -21,6 | -21,6 |
| EINKO7 | 37 | , | 37 | 37 |
| EINKO8 | 100 | , | 100 | 100 |
| EINKO9 | -40,2 | , | -40,2 | -40,2 |
| EINKO10 | 24,8 | , | 24,8 | 24,8 |
| PKWHH | 65,5 | 57,7 | 65,5 | 47 |
| SEX1 | 50,4 | , | 50,4 | 50,4 |
| SEX2 | 50,4 | , | 50,4 | 50,4 |
| ALTER1 | 100 | , | 100 | 100 |
| ALTER2 | 34,8 | , | 34,8 | 34,8 |
| ALTER3 | 68,9 | , | 68,9 | 68,9 |
| ALTER4 | 52,9 | , | 52,9 | 52,9 |
| ALTER5 | 100 | , | 100 | 100 |
| ALTER6 | 100 | , | 100 | 100 |
| ALTER7 | 100 | , | 100 | 100 |
| SCHULAB1 | 60 | , | 60 | 60 |
| SCHULAB2 | 61,2 | , | 61,2 | 61,2 |
| SCHULAB3 | 100 | , | 100 | 100 |
| BERUF1 | 94,8 | , | 94,8 | 94,8 |
| BERUF2 | 66,3 | , | 66,3 | 66,3 |
| BERUF3 | 47,9 | , | 47,9 | 47,9 |
| BERUF4 | 100 | , | 100 | 100 |
| FSPKW0 | 100 | , | 100 | 100 |
| FSPKW1 | 100 | , | 100 | 100 |
| P,T,card0 | 72,2 | , | 72,2 | 72,2 |
| P,T,card1 | 72,2 | , | 72,2 | 72,2 |

**Table A. C–7**
Summary of balance for all data (2014)

| Covariate | Means Treated | Means Control | Std. Mean Diff | Var. Ratio | eCDF Mean | eCDF Max |
|---|---|---|---|---|---|---|
| distance | 0,432 | 0,008 | 1,594 | 32,533 | 0,671 | 0,883 |
| RAUMTYP1 | 1,000 | 0,462 | 1,078 | , | 0,538 | 0,538 |
| RAUMTYP2 | 0,000 | 0,231 | -0,550 | , | 0,231 | 0,231 |
| RAUMTYP3 | 0,000 | 0,195 | -0,494 | , | 0,195 | 0,195 |
| RAUMTYP4 | 0,000 | 0,078 | -0,292 | , | 0,078 | 0,078 |
| RAUMTYP5 | 0,000 | 0,035 | -0,192 | , | 0,035 | 0,035 |
| HHGRO | 1,750 | 2,141 | -0,421 | 0,766 | 0,065 | 0,210 |
| P0_10 | 0,188 | 0,157 | 0,057 | 1,186 | 0,009 | 0,021 |
| EINKO1 | 0,063 | 0,013 | 0,206 | , | 0,050 | 0,050 |
| EINKO2 | 0,000 | 0,036 | -0,195 | , | 0,036 | 0,036 |
| EINKO3 | 0,000 | 0,083 | -0,303 | , | 0,083 | 0,083 |
| EINKO4 | 0,375 | 0,136 | 0,494 | , | 0,239 | 0,239 |
| EINKO5 | 0,063 | 0,132 | -0,285 | , | 0,069 | 0,069 |
| EINKO6 | 0,188 | 0,125 | 0,160 | , | 0,062 | 0,062 |
| EINKO7 | 0,125 | 0,132 | -0,020 | , | 0,007 | 0,007 |
| EINKO8 | 0,063 | 0,090 | -0,114 | , | 0,028 | 0,028 |
| EINKO9 | 0,063 | 0,122 | -0,244 | , | 0,059 | 0,059 |
| EINKO10 | 0,063 | 0,132 | -0,289 | , | 0,070 | 0,070 |
| PKWHH | 0,188 | 1,347 | -2,876 | 0,264 | 0,193 | 0,704 |
| SEX1 | 0,563 | 0,507 | 0,112 | , | 0,055 | 0,055 |
| SEX2 | 0,438 | 0,493 | -0,112 | , | 0,055 | 0,055 |
| ALTER1 | 0,000 | 0,001 | -0,030 | , | 0,001 | 0,001 |
| ALTER2 | 0,188 | 0,035 | 0,390 | , | 0,152 | 0,152 |
| ALTER3 | 0,375 | 0,090 | 0,589 | , | 0,285 | 0,285 |
| ALTER4 | 0,125 | 0,274 | -0,450 | , | 0,149 | 0,149 |
| ALTER5 | 0,250 | 0,259 | -0,020 | , | 0,009 | 0,009 |
| ALTER6 | 0,000 | 0,209 | -0,517 | , | 0,209 | 0,209 |
| ALTER7 | 0,063 | 0,132 | -0,289 | , | 0,070 | 0,070 |
| SCHULAB1 | 0,375 | 0,481 | -0,219 | , | 0,106 | 0,106 |
| SCHULAB2 | 0,625 | 0,516 | 0,225 | , | 0,109 | 0,109 |
| SCHULAB3 | 0,000 | 0,003 | -0,052 | , | 0,003 | 0,003 |
| BERUF1 | 0,438 | 0,444 | -0,013 | , | 0,007 | 0,007 |
| BERUF2 | 0,188 | 0,209 | -0,055 | , | 0,022 | 0,022 |
| BERUF3 | 0,313 | 0,043 | 0,581 | , | 0,269 | 0,269 |
| BERUF4 | 0,063 | 0,304 | -0,996 | , | 0,241 | 0,241 |
| FSPKW0 | 0,000 | 0,051 | -0,234 | , | 0,051 | 0,051 |
| FSPKW1 | 1,000 | 0,949 | 0,234 | , | 0,051 | 0,051 |
| P,T,card0 | 0,063 | 0,753 | -2,853 | , | 0,691 | 0,691 |
| P,T,card1 | 0,938 | 0,247 | 2,853 | , | 0,691 | 0,691 |

**Table A. C–8**

Summary of balance for matched data (2014)

| Covariate | Means Treated | Means Control | Std. Mean Diff | Var. Ratio | eCDF Mean | eCDF Max | Std. Pair Dist. |
|---|---|---|---|---|---|---|---|
| distance | 0,432 | 0,106 | 1,227 | 3,523 | 0,050 | 0,613 | 1,229 |
| RAUMTYP1 | 1,000 | 1,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| RAUMTYP2 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| RAUMTYP3 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| RAUMTYP4 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| RAUMTYP5 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| HHGRO | 1,750 | 1,863 | -0,121 | 0,801 | 0,019 | 0,063 | 1,007 |
| P0_10 | 0,188 | 0,213 | -0,046 | 0,999 | 0,005 | 0,025 | 0,644 |
| EINKO1 | 0,063 | 0,050 | 0,052 | , | 0,013 | 0,013 | 0,465 |
| EINKO2 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| EINKO3 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| EINKO4 | 0,375 | 0,200 | 0,362 | , | 0,175 | 0,175 | 0,775 |
| EINKO5 | 0,063 | 0,100 | -0,155 | , | 0,038 | 0,038 | 0,671 |
| EINKO6 | 0,188 | 0,175 | 0,032 | , | 0,013 | 0,013 | 0,737 |
| EINKO7 | 0,125 | 0,225 | -0,302 | , | 0,100 | 0,100 | 0,680 |
| EINKO8 | 0,063 | 0,113 | -0,207 | , | 0,050 | 0,050 | 0,723 |
| EINKO9 | 0,063 | 0,088 | -0,103 | , | 0,025 | 0,025 | 0,620 |
| EINKO10 | 0,063 | 0,050 | 0,052 | , | 0,013 | 0,013 | 0,465 |
| PKWHH | 0,188 | 0,600 | -1,023 | 0,669 | 0,069 | 0,413 | 1,209 |
| SEX1 | 0,563 | 0,525 | 0,076 | , | 0,038 | 0,038 | 0,983 |
| SEX2 | 0,438 | 0,475 | -0,076 | , | 0,038 | 0,038 | 0,983 |
| ALTER1 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| ALTER2 | 0,188 | 0,050 | 0,352 | , | 0,138 | 0,138 | 0,609 |
| ALTER3 | 0,375 | 0,325 | 0,103 | , | 0,050 | 0,050 | 0,981 |
| ALTER4 | 0,125 | 0,250 | -0,378 | , | 0,125 | 0,125 | 1,058 |
| ALTER5 | 0,250 | 0,238 | 0,029 | , | 0,013 | 0,013 | 0,895 |
| ALTER6 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| ALTER7 | 0,063 | 0,138 | -0,310 | , | 0,075 | 0,075 | 0,826 |
| SCHULAB1 | 0,375 | 0,300 | 0,155 | , | 0,075 | 0,075 | 1,084 |
| SCHULAB2 | 0,625 | 0,700 | -0,155 | , | 0,075 | 0,075 | 1,084 |
| SCHULAB3 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| BERUF1 | 0,438 | 0,563 | -0,252 | , | 0,125 | 0,125 | 1,008 |
| BERUF2 | 0,188 | 0,188 | 0,000 | , | 0,000 | 0,000 | 0,325 |
| BERUF3 | 0,313 | 0,113 | 0,432 | , | 0,200 | 0,200 | 0,701 |
| BERUF4 | 0,063 | 0,138 | -0,310 | , | 0,075 | 0,075 | 0,826 |
| FSPKW0 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| FSPKW1 | 1,000 | 1,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| P,T,card0 | 0,063 | 0,238 | -0,723 | , | 0,175 | 0,175 | 0,723 |
| P,T,card1 | 0,938 | 0,763 | 0,723 | , | 0,175 | 0,175 | 0,723 |

**Table A. C–9**

Percent balance improvement (2014)

| Covariate | Std. Mean Diff | Var. Ratio | eCDF Mean | eCDF Max |
|---|---|---|---|---|
| distance | 23 | 63,8 | 92,5 | 30,6 |
| RAUMTYP1 | 100 | , | 100 | 100 |
| RAUMTYP2 | 100 | , | 100 | 100 |
| RAUMTYP3 | 100 | , | 100 | 100 |
| RAUMTYP4 | 100 | , | 100 | 100 |
| RAUMTYP5 | 100 | , | 100 | 100 |
| HHGRO | 71,3 | 16,7 | 71,3 | 70,2 |
| P0_10 | 18,7 | 99,6 | 46,8 | -18,7 |
| EINKO1 | 74,9 | , | 74,9 | 74,9 |
| EINKO2 | 100 | , | 100 | 100 |
| EINKO3 | 100 | , | 100 | 100 |
| EINKO4 | 26,8 | , | 26,8 | 26,8 |
| EINKO5 | 45,7 | , | 45,7 | 45,7 |
| EINKO6 | 79,9 | , | 79,9 | 79,9 |
| EINKO7 | -1431 | , | -1431 | -1431 |
| EINKO8 | -81,2 | , | -81,2 | -81,2 |
| EINKO9 | 57,7 | , | 57,7 | 57,7 |
| EINKO10 | 82,1 | , | 82,1 | 82,1 |
| PKWHH | 64,4 | 69,7 | 64,4 | 41,4 |
| SEX1 | 32,2 | , | 32,2 | 32,2 |
| SEX2 | 32,2 | , | 32,2 | 32,2 |
| ALTER1 | 100 | , | 100 | 100 |
| ALTER2 | 9,8 | , | 9,8 | 9,8 |
| ALTER3 | 82,5 | , | 82,5 | 82,5 |
| ALTER4 | 16 | , | 16 | 16 |
| ALTER5 | -46,1 | , | -46,1 | -46,1 |
| ALTER6 | 100 | , | 100 | 100 |
| ALTER7 | -7,2 | , | -7,2 | -7,2 |
| SCHULAB1 | 29,3 | , | 29,3 | 29,3 |
| SCHULAB2 | 31,1 | , | 31,1 | 31,1 |
| SCHULAB3 | 100 | , | 100 | 100 |
| BERUF1 | -1781,4 | , | -1781,4 | -1781,4 |
| BERUF2 | 100 | , | 100 | 100 |
| BERUF3 | 25,7 | , | 25,7 | 25,7 |
| BERUF4 | 68,9 | , | 68,9 | 68,9 |
| FSPKW0 | 100 | , | 100 | 100 |
| FSPKW1 | 100 | , | 100 | 100 |
| P,T,card0 | 74,7 | , | 74,7 | 74,7 |
| P,T,card1 | 74,7 | , | 74,7 | 74,7 |

**Table A. C–10**
Summary of balance for all data (2015)

| Covariate | Means Treated | Means Control | Std. Mean Diff | Var. Ratio | eCDF Mean | eCDF Max |
|---|---|---|---|---|---|---|
| distance | 0,512 | 0,007 | 1,503 | 61,063 | 0,729 | 0,953 |
| RAUMTYP1 | 1,000 | 0,447 | 1,111 | , | 0,553 | 0,553 |
| RAUMTYP2 | 0,000 | 0,225 | -0,542 | , | 0,225 | 0,225 |
| RAUMTYP3 | 0,000 | 0,201 | -0,505 | , | 0,201 | 0,201 |
| RAUMTYP4 | 0,000 | 0,082 | -0,302 | , | 0,082 | 0,082 |
| RAUMTYP5 | 0,000 | 0,044 | -0,216 | , | 0,044 | 0,044 |
| HHGRO | 2,188 | 2,100 | 0,083 | 0,981 | 0,024 | 0,129 |
| P0_10 | 0,250 | 0,143 | 0,186 | 1,474 | 0,030 | 0,090 |
| EINKO1 | 0,063 | 0,004 | 0,241 | , | 0,058 | 0,058 |
| EINKO2 | 0,063 | 0,036 | 0,111 | , | 0,027 | 0,027 |
| EINKO3 | 0,063 | 0,089 | -0,110 | , | 0,027 | 0,027 |
| EINKO4 | 0,125 | 0,160 | -0,105 | , | 0,035 | 0,035 |
| EINKO5 | 0,063 | 0,128 | -0,272 | , | 0,066 | 0,066 |
| EINKO6 | 0,125 | 0,137 | -0,036 | , | 0,012 | 0,012 |
| EINKO7 | 0,125 | 0,109 | 0,049 | , | 0,016 | 0,016 |
| EINKO8 | 0,125 | 0,105 | 0,062 | , | 0,021 | 0,021 |
| EINKO9 | 0,125 | 0,112 | 0,039 | , | 0,013 | 0,013 |
| EINKO10 | 0,125 | 0,121 | 0,013 | , | 0,004 | 0,004 |
| PKWHH | 0,125 | 1,347 | -3,577 | 0,173 | 0,175 | 0,756 |
| SEX1 | 0,500 | 0,520 | -0,040 | , | 0,020 | 0,020 |
| SEX2 | 0,500 | 0,480 | 0,040 | , | 0,020 | 0,020 |
| ALTER1 | 0,000 | 0,003 | -0,059 | , | 0,003 | 0,003 |
| ALTER2 | 0,188 | 0,033 | 0,396 | , | 0,154 | 0,154 |
| ALTER3 | 0,500 | 0,087 | 0,827 | , | 0,413 | 0,413 |
| ALTER4 | 0,125 | 0,254 | -0,390 | , | 0,129 | 0,129 |
| ALTER5 | 0,188 | 0,280 | -0,238 | , | 0,093 | 0,093 |
| ALTER6 | 0,000 | 0,212 | -0,521 | , | 0,212 | 0,212 |
| ALTER7 | 0,000 | 0,131 | -0,390 | , | 0,131 | 0,131 |
| SCHULAB1 | 0,313 | 0,485 | -0,372 | , | 0,173 | 0,173 |
| SCHULAB2 | 0,688 | 0,511 | 0,382 | , | 0,177 | 0,177 |
| SCHULAB3 | 0,000 | 0,004 | -0,066 | , | 0,004 | 0,004 |
| BERUF1 | 0,563 | 0,462 | 0,202 | , | 0,100 | 0,100 |
| BERUF2 | 0,313 | 0,195 | 0,253 | , | 0,117 | 0,117 |
| BERUF3 | 0,125 | 0,036 | 0,270 | , | 0,089 | 0,089 |
| BERUF4 | 0,000 | 0,307 | -0,668 | , | 0,307 | 0,307 |
| FSPKW0 | 0,000 | 0,060 | -0,255 | , | 0,060 | 0,060 |
| FSPKW1 | 1,000 | 0,940 | 0,255 | , | 0,060 | 0,060 |
| P,T,card0 | 0,063 | 0,760 | -2,883 | , | 0,698 | 0,698 |
| P,T,card1 | 0,938 | 0,240 | 2,883 | , | 0,698 | 0,698 |

**Table A. C–11**
Summary of balance for matched data (2015)

| Covariate | Means Treated | Means Control | Std. Mean Diff | Var. Ratio | eCDF Mean | eCDF Max | Std. Pair Dist. |
|---|---|---|---|---|---|---|---|
| distance | 0,512 | 0,096 | 1,236 | 5,998 | 0,064 | 0,663 | 1,237 |
| RAUMTYP1 | 1,000 | 1,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| RAUMTYP2 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| RAUMTYP3 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| RAUMTYP4 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| RAUMTYP5 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| HHGRO | 2,188 | 2,300 | -0,108 | 0,741 | 0,020 | 0,088 | 1,063 |
| P0_10 | 0,250 | 0,238 | 0,022 | 1,171 | 0,003 | 0,013 | 0,715 |
| EINKO1 | 0,063 | 0,025 | 0,155 | , | 0,038 | 0,038 | 0,362 |
| EINKO2 | 0,063 | 0,063 | 0,000 | , | 0,000 | 0,000 | 0,100 |
| EINKO3 | 0,063 | 0,100 | -0,155 | , | 0,038 | 0,038 | 0,671 |
| EINKO4 | 0,125 | 0,125 | 0,000 | , | 0,000 | 0,000 | 0,250 |
| EINKO5 | 0,063 | 0,088 | -0,103 | , | 0,025 | 0,025 | 0,620 |
| EINKO6 | 0,125 | 0,075 | 0,151 | , | 0,050 | 0,050 | 0,605 |
| EINKO7 | 0,125 | 0,088 | 0,113 | , | 0,038 | 0,038 | 0,643 |
| EINKO8 | 0,125 | 0,088 | 0,113 | , | 0,038 | 0,038 | 0,643 |
| EINKO9 | 0,125 | 0,175 | -0,151 | , | 0,050 | 0,050 | 0,832 |
| EINKO10 | 0,125 | 0,175 | -0,151 | , | 0,050 | 0,050 | 0,756 |
| PKWHH | 0,125 | 0,513 | -1,135 | 0,419 | 0,055 | 0,375 | 1,281 |
| SEX1 | 0,500 | 0,463 | 0,075 | , | 0,038 | 0,038 | 1,025 |
| SEX2 | 0,500 | 0,538 | -0,075 | , | 0,038 | 0,038 | 1,025 |
| ALTER1 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| ALTER2 | 0,188 | 0,075 | 0,288 | , | 0,113 | 0,113 | 0,609 |
| ALTER3 | 0,500 | 0,275 | 0,450 | , | 0,225 | 0,225 | 0,850 |
| ALTER4 | 0,125 | 0,350 | -0,680 | , | 0,225 | 0,225 | 0,983 |
| ALTER5 | 0,188 | 0,300 | -0,288 | , | 0,113 | 0,113 | 0,865 |
| ALTER6 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| ALTER7 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| SCHULAB1 | 0,313 | 0,275 | 0,081 | , | 0,038 | 0,038 | 0,944 |
| SCHULAB2 | 0,688 | 0,725 | -0,081 | , | 0,038 | 0,038 | 0,944 |
| SCHULAB3 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| BERUF1 | 0,563 | 0,600 | -0,076 | , | 0,038 | 0,038 | 1,235 |
| BERUF2 | 0,313 | 0,338 | -0,054 | , | 0,025 | 0,025 | 1,025 |
| BERUF3 | 0,125 | 0,063 | 0,189 | , | 0,063 | 0,063 | 0,567 |
| BERUF4 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| FSPKW0 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| FSPKW1 | 1,000 | 1,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| P,T,card0 | 0,063 | 0,300 | -0,981 | , | 0,238 | 0,238 | 1,188 |
| P,T,card1 | 0,938 | 0,700 | 0,981 | , | 0,238 | 0,238 | 1,188 |

**Table A. C–12**

Percent balance improvement (2015)

| Covariate | Std. Mean Diff | Var. Ratio | eCDF Mean | eCDF Max |
|---|---|---|---|---|
| distance | 17,7 | 56,4 | 91,2 | 30,5 |
| RAUMTYP1 | 100 | , | 100 | 100 |
| RAUMTYP2 | 100 | , | 100 | 100 |
| RAUMTYP3 | 100 | , | 100 | 100 |
| RAUMTYP4 | 100 | , | 100 | 100 |
| RAUMTYP5 | 100 | , | 100 | 100 |
| HHGRO | -28,9 | -1430,3 | 19,1 | 32 |
| P0_10 | 88,3 | 59,3 | 89,7 | 86,1 |
| EINKO1 | 35,6 | , | 35,6 | 35,6 |
| EINKO2 | 100 | , | 100 | 100 |
| EINKO3 | -40,4 | , | -40,4 | -40,4 |
| EINKO4 | 100 | , | 100 | 100 |
| EINKO5 | 62 | , | 62 | 62 |
| EINKO6 | -324,1 | , | -324,1 | -324,1 |
| EINKO7 | -130,8 | , | -130,8 | -130,8 |
| EINKO8 | -83 | , | -83 | -83 |
| EINKO9 | -289,1 | , | -289,1 | -289,1 |
| EINKO10 | -1048,3 | , | -1048,3 | -1048,3 |
| PKWHH | 68,3 | 50,4 | 68,3 | 50,4 |
| SEX1 | -87,8 | , | -87,8 | -87,8 |
| SEX2 | -87,8 | , | -87,8 | -87,8 |
| ALTER1 | 100 | , | 100 | 100 |
| ALTER2 | 27,1 | , | 27,1 | 27,1 |
| ALTER3 | 45,6 | , | 45,6 | 45,6 |
| ALTER4 | -74,4 | , | -74,4 | -74,4 |
| ALTER5 | -21,1 | , | -21,1 | -21,1 |
| ALTER6 | 100 | , | 100 | 100 |
| ALTER7 | 100 | , | 100 | 100 |
| SCHULAB1 | 78,3 | , | 78,3 | 78,3 |
| SCHULAB2 | 78,8 | , | 78,8 | 78,8 |
| SCHULAB3 | 100 | , | 100 | 100 |
| BERUF1 | 62,6 | , | 62,6 | 62,6 |
| BERUF2 | 78,6 | , | 78,6 | 78,6 |
| BERUF3 | 30 | , | 30 | 30 |
| BERUF4 | 100 | , | 100 | 100 |
| FSPKW0 | 100 | , | 100 | 100 |
| FSPKW1 | 100 | , | 100 | 100 |
| P,T,card0 | 66 | , | 66 | 66 |
| P,T,card1 | 66 | , | 66 | 66 |

**Table A. C–13**

Summary of balance for all data (2016)

| Covariate | Means Treated | Means Control | Std. Mean Diff | Var. Ratio | eCDF Mean | eCDF Max |
|---|---|---|---|---|---|---|
| distance | 0,327 | 0,010 | 1,227 | 29,538 | 0,533 | 0,839 |
| RAUMTYP1 | 0,905 | 0,450 | 1,551 | , | 0,455 | 0,455 |
| RAUMTYP2 | 0,048 | 0,226 | -0,835 | , | 0,178 | 0,178 |
| RAUMTYP3 | 0,048 | 0,209 | -0,759 | , | 0,162 | 0,162 |
| RAUMTYP4 | 0,000 | 0,072 | -0,281 | , | 0,072 | 0,072 |
| RAUMTYP5 | 0,000 | 0,044 | -0,215 | , | 0,044 | 0,044 |
| HHGRO | 2,381 | 2,063 | 0,367 | 0,684 | 0,076 | 0,239 |
| P0_10 | 0,286 | 0,135 | 0,234 | 1,896 | 0,040 | 0,101 |
| EINKO1 | 0,000 | 0,006 | -0,078 | , | 0,006 | 0,006 |
| EINKO2 | 0,000 | 0,036 | -0,195 | , | 0,036 | 0,036 |
| EINKO3 | 0,048 | 0,091 | -0,206 | , | 0,044 | 0,044 |
| EINKO4 | 0,095 | 0,132 | -0,125 | , | 0,037 | 0,037 |
| EINKO5 | 0,191 | 0,147 | 0,110 | , | 0,043 | 0,043 |
| EINKO6 | 0,095 | 0,113 | -0,060 | , | 0,018 | 0,018 |
| EINKO7 | 0,143 | 0,136 | 0,021 | , | 0,007 | 0,007 |
| EINKO8 | 0,048 | 0,105 | -0,268 | , | 0,057 | 0,057 |
| EINKO9 | 0,143 | 0,106 | 0,105 | , | 0,037 | 0,037 |
| EINKO10 | 0,238 | 0,128 | 0,258 | , | 0,110 | 0,110 |
| PKWHH | 0,476 | 1,311 | -1,388 | 0,498 | 0,119 | 0,431 |
| SEX1 | 0,476 | 0,530 | -0,107 | , | 0,054 | 0,054 |
| SEX2 | 0,524 | 0,470 | 0,107 | , | 0,054 | 0,054 |
| ALTER1 | 0,000 | 0,014 | -0,120 | , | 0,014 | 0,014 |
| ALTER2 | 0,095 | 0,022 | 0,249 | , | 0,073 | 0,073 |
| ALTER3 | 0,524 | 0,074 | 0,900 | , | 0,449 | 0,449 |
| ALTER4 | 0,191 | 0,210 | -0,050 | , | 0,020 | 0,020 |
| ALTER5 | 0,000 | 0,267 | -0,606 | , | 0,267 | 0,267 |
| ALTER6 | 0,191 | 0,228 | -0,095 | , | 0,037 | 0,037 |
| ALTER7 | 0,000 | 0,185 | -0,479 | , | 0,185 | 0,185 |
| SCHULAB1 | 0,143 | 0,505 | -1,034 | , | 0,362 | 0,362 |
| SCHULAB2 | 0,762 | 0,484 | 0,652 | , | 0,278 | 0,278 |
| SCHULAB3 | 0,095 | 0,011 | 0,287 | , | 0,084 | 0,084 |
| BERUF1 | 0,524 | 0,425 | 0,199 | , | 0,099 | 0,099 |
| BERUF2 | 0,238 | 0,158 | 0,187 | , | 0,080 | 0,080 |
| BERUF3 | 0,143 | 0,041 | 0,292 | , | 0,102 | 0,102 |
| BERUF4 | 0,095 | 0,377 | -0,958 | , | 0,281 | 0,281 |
| FSPKW0 | 0,000 | 0,085 | -0,306 | , | 0,085 | 0,085 |
| FSPKW1 | 1,000 | 0,915 | 0,306 | , | 0,085 | 0,085 |
| P,T,card0 | 0,333 | 0,749 | -0,881 | , | 0,415 | 0,415 |
| P,T,card1 | 0,667 | 0,251 | 0,881 | , | 0,415 | 0,415 |

**Table A. C–14**

Summary of balance for matched data (2016)

| Covariate | Means Treated | Means Control | Std. Mean Diff | Var. Ratio | eCDF Mean | eCDF Max | Std. Pair Dist. |
|---|---|---|---|---|---|---|---|
| distance | 0,327 | 0,116 | 0,818 | 3,920 | 0,030 | 0,533 | 0,821 |
| RAUMTYP1 | 0,905 | 0,848 | 0,195 | , | 0,057 | 0,057 | 0,714 |
| RAUMTYP2 | 0,048 | 0,067 | -0,089 | , | 0,019 | 0,019 | 0,537 |
| RAUMTYP3 | 0,048 | 0,086 | -0,179 | , | 0,038 | 0,038 | 0,626 |
| RAUMTYP4 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| RAUMTYP5 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| HHGRO | 2,381 | 2,257 | 0,143 | 0,670 | 0,040 | 0,152 | 1,179 |
| P0_10 | 0,286 | 0,257 | 0,044 | 1,195 | 0,007 | 0,019 | 0,755 |
| EINKO1 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| EINKO2 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| EINKO3 | 0,048 | 0,057 | -0,045 | , | 0,010 | 0,010 | 0,492 |
| EINKO4 | 0,095 | 0,152 | -0,195 | , | 0,057 | 0,057 | 0,844 |
| EINKO5 | 0,191 | 0,124 | 0,170 | , | 0,067 | 0,067 | 0,800 |
| EINKO6 | 0,095 | 0,105 | -0,032 | , | 0,010 | 0,010 | 0,616 |
| EINKO7 | 0,143 | 0,114 | 0,082 | , | 0,029 | 0,029 | 0,735 |
| EINKO8 | 0,048 | 0,057 | -0,045 | , | 0,010 | 0,010 | 0,403 |
| EINKO9 | 0,143 | 0,152 | -0,027 | , | 0,010 | 0,010 | 0,789 |
| EINKO10 | 0,238 | 0,238 | 0,000 | , | 0,000 | 0,000 | 0,343 |
| PKWHH | 0,476 | 0,629 | -0,253 | 1,320 | 0,030 | 0,181 | 0,918 |
| SEX1 | 0,476 | 0,571 | -0,191 | , | 0,095 | 0,095 | 0,839 |
| SEX2 | 0,524 | 0,429 | 0,191 | , | 0,095 | 0,095 | 0,839 |
| ALTER1 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| ALTER2 | 0,095 | 0,076 | 0,065 | , | 0,019 | 0,019 | 0,584 |
| ALTER3 | 0,524 | 0,305 | 0,439 | , | 0,219 | 0,219 | 0,973 |
| ALTER4 | 0,191 | 0,295 | -0,267 | , | 0,105 | 0,105 | 1,091 |
| ALTER5 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| ALTER6 | 0,191 | 0,324 | -0,340 | , | 0,133 | 0,133 | 0,825 |
| ALTER7 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| SCHULAB1 | 0,143 | 0,276 | -0,381 | , | 0,133 | 0,133 | 0,980 |
| SCHULAB2 | 0,762 | 0,714 | 0,112 | , | 0,048 | 0,048 | 1,006 |
| SCHULAB3 | 0,095 | 0,010 | 0,292 | , | 0,086 | 0,086 | 0,357 |
| BERUF1 | 0,524 | 0,571 | -0,095 | , | 0,048 | 0,048 | 1,011 |
| BERUF2 | 0,238 | 0,162 | 0,179 | , | 0,076 | 0,076 | 0,850 |
| BERUF3 | 0,143 | 0,076 | 0,191 | , | 0,067 | 0,067 | 0,517 |
| BERUF4 | 0,095 | 0,191 | -0,324 | , | 0,095 | 0,095 | 0,714 |
| FSPKW0 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| FSPKW1 | 1,000 | 1,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| P,T,card0 | 0,333 | 0,410 | -0,162 | , | 0,076 | 0,076 | 1,051 |
| P,T,card1 | 0,6667 | 0,5905 | 0,1616 | , | 0,0762 | 0,0762 | 1,0506 |

**Table A. C–15**

Percent balance improvement (2016)

| Covariate | Std. Mean Diff | Var. Ratio | eCDF Mean | eCDF Max |
|---|---|---|---|---|
| distance | 33,3 | 59,7 | 94,5 | 36,4 |
| RAUMTYP1 | 87,4 | , | 87,4 | 87,4 |
| RAUMTYP2 | 89,3 | , | 89,3 | 89,3 |
| RAUMTYP3 | 76,4 | , | 76,4 | 76,4 |
| RAUMTYP4 | 100 | , | 100 | 100 |
| RAUMTYP5 | 100 | , | 100 | 100 |
| HHGRO | 61 | -5,4 | 47,1 | 36,3 |
| P0_10 | 81,1 | 72,2 | 82,3 | 81,2 |
| EINKO1 | 100 | , | 100 | 100 |
| EINKO2 | 100 | , | 100 | 100 |
| EINKO3 | 78,2 | , | 78,2 | 78,2 |
| EINKO4 | -55,8 | , | -55,8 | -55,8 |
| EINKO5 | -54,7 | , | -54,7 | -54,7 |
| EINKO6 | 45,6 | , | 45,6 | 45,6 |
| EINKO7 | -293,3 | , | -293,3 | -293,3 |
| EINKO8 | 83,3 | , | 83,3 | 83,3 |
| EINKO9 | 74,1 | , | 74,1 | 74,1 |
| EINKO10 | 100 | , | 100 | 100 |
| PKWHH | 81,7 | 60,1 | 74,9 | 58,1 |
| SEX1 | -77,5 | , | -77,5 | -77,5 |
| SEX2 | -77,5 | , | -77,5 | -77,5 |
| ALTER1 | 100 | , | 100 | 100 |
| ALTER2 | 74 | , | 74 | 74 |
| ALTER3 | 51,3 | , | 51,3 | 51,3 |
| ALTER4 | -436 | , | -436 | -436 |
| ALTER5 | 100 | , | 100 | 100 |
| ALTER6 | -258,1 | , | -258,1 | -258,1 |
| ALTER7 | 100 | , | 100 | 100 |
| SCHULAB1 | 63,2 | , | 63,2 | 63,2 |
| SCHULAB2 | 82,9 | , | 82,9 | 82,9 |
| SCHULAB3 | -1,8 | , | -1,8 | -1,8 |
| BERUF1 | 52,1 | , | 52,1 | 52,1 |
| BERUF2 | 4,4 | , | 4,4 | 4,4 |
| BERUF3 | 34,8 | , | 34,8 | 34,8 |
| BERUF4 | 66,1 | , | 66,1 | 66,1 |
| FSPKW0 | 100 | , | 100 | 100 |
| FSPKW1 | 100 | , | 100 | 100 |
| P,T,card0 | 81,7 | , | 81,7 | 81,7 |
| P,T,card1 | 81,7 | , | 81,7 | 81,7 |

**Table A. C–16**

Summary of balance for all data (2017)

| Covariate | Means Treated | Means Control | Std. Mean Diff | Var. Ratio | eCDF Mean | eCDF Max |
|---|---|---|---|---|---|---|
| distance | 0,185 | 0,018 | 1,034 | 10,111 | 0,446 | 0,749 |
| RAUMTYP1 | 0,903 | 0,451 | 1,530 | , | 0,452 | 0,452 |
| RAUMTYP2 | 0,065 | 0,239 | -0,710 | , | 0,174 | 0,174 |
| RAUMTYP3 | 0,032 | 0,204 | -0,974 | , | 0,172 | 0,172 |
| RAUMTYP4 | 0,000 | 0,064 | -0,263 | , | 0,064 | 0,064 |
| RAUMTYP5 | 0,000 | 0,042 | -0,212 | , | 0,042 | 0,042 |
| HHGRO | 2,484 | 2,088 | 0,344 | 1,173 | 0,079 | 0,228 |
| P0_10 | 0,484 | 0,144 | 0,419 | 2,896 | 0,085 | 0,223 |
| EINKO1 | 0,000 | 0,006 | -0,080 | , | 0,006 | 0,006 |
| EINKO2 | 0,032 | 0,044 | -0,064 | , | 0,011 | 0,011 |
| EINKO3 | 0,000 | 0,097 | -0,330 | , | 0,097 | 0,097 |
| EINKO4 | 0,097 | 0,137 | -0,138 | , | 0,041 | 0,041 |
| EINKO5 | 0,161 | 0,138 | 0,063 | , | 0,023 | 0,023 |
| EINKO6 | 0,129 | 0,118 | 0,033 | , | 0,011 | 0,011 |
| EINKO7 | 0,129 | 0,116 | 0,039 | , | 0,013 | 0,013 |
| EINKO8 | 0,032 | 0,102 | -0,396 | , | 0,070 | 0,070 |
| EINKO9 | 0,194 | 0,127 | 0,168 | , | 0,067 | 0,067 |
| EINKO10 | 0,226 | 0,115 | 0,266 | , | 0,111 | 0,111 |
| PKWHH | 0,548 | 1,295 | -1,106 | 0,606 | 0,107 | 0,401 |
| SEX1 | 0,613 | 0,506 | 0,219 | , | 0,107 | 0,107 |
| SEX2 | 0,387 | 0,494 | -0,219 | , | 0,107 | 0,107 |
| ALTER1 | 0,000 | 0,002 | -0,046 | , | 0,002 | 0,002 |
| ALTER2 | 0,032 | 0,024 | 0,046 | , | 0,008 | 0,008 |
| ALTER3 | 0,323 | 0,077 | 0,525 | , | 0,245 | 0,245 |
| ALTER4 | 0,290 | 0,193 | 0,215 | , | 0,098 | 0,098 |
| ALTER5 | 0,226 | 0,289 | -0,150 | , | 0,063 | 0,063 |
| ALTER6 | 0,097 | 0,224 | -0,430 | , | 0,127 | 0,127 |
| ALTER7 | 0,032 | 0,191 | -0,900 | , | 0,159 | 0,159 |
| SCHULAB1 | 0,161 | 0,501 | -0,925 | , | 0,340 | 0,340 |
| SCHULAB2 | 0,839 | 0,493 | 0,940 | , | 0,346 | 0,346 |
| SCHULAB3 | 0,000 | 0,006 | -0,075 | , | 0,006 | 0,006 |
| BERUF1 | 0,613 | 0,408 | 0,420 | , | 0,205 | 0,205 |
| BERUF2 | 0,226 | 0,192 | 0,081 | , | 0,034 | 0,034 |
| BERUF3 | 0,065 | 0,030 | 0,142 | , | 0,035 | 0,035 |
| BERUF4 | 0,097 | 0,370 | -0,925 | , | 0,273 | 0,273 |
| FSPKW0 | 0,000 | 0,055 | -0,243 | , | 0,055 | 0,055 |
| FSPKW1 | 1,000 | 0,945 | 0,243 | , | 0,055 | 0,055 |
| P,T,card0 | 0,226 | 0,728 | -1,201 | , | 0,502 | 0,502 |
| P,T,card1 | 0,774 | 0,272 | 1,201 | , | 0,502 | 0,502 |

**Table A. C–17**

Summary of balance for matched data (2017)

| Covariate | Means Treated | Means Control | Std. Mean Diff | Var. Ratio | eCDF Mean | eCDF Max | Std. Pair Dist. |
|---|---|---|---|---|---|---|---|
| distance | 0,185 | 0,120 | 0,399 | 2,213 | 0,015 | 0,284 | 0,406 |
| RAUMTYP1 | 0,903 | 0,884 | 0,066 | , | 0,019 | 0,019 | 0,589 |
| RAUMTYP2 | 0,065 | 0,097 | -0,131 | , | 0,032 | 0,032 | 0,552 |
| RAUMTYP3 | 0,032 | 0,019 | 0,073 | , | 0,013 | 0,013 | 0,292 |
| RAUMTYP4 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| RAUMTYP5 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| HHGRO | 2,484 | 2,387 | 0,084 | 0,941 | 0,035 | 0,116 | 1,037 |
| P0_10 | 0,484 | 0,407 | 0,095 | 1,062 | 0,019 | 0,071 | 0,907 |
| EINKO1 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| EINKO2 | 0,032 | 0,039 | -0,037 | , | 0,007 | 0,007 | 0,329 |
| EINKO3 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| EINKO4 | 0,097 | 0,090 | 0,022 | , | 0,007 | 0,007 | 0,502 |
| EINKO5 | 0,161 | 0,161 | 0,000 | , | 0,000 | 0,000 | 0,245 |
| EINKO6 | 0,129 | 0,110 | 0,058 | , | 0,019 | 0,019 | 0,635 |
| EINKO7 | 0,129 | 0,142 | -0,039 | , | 0,013 | 0,013 | 0,577 |
| EINKO8 | 0,032 | 0,045 | -0,073 | , | 0,013 | 0,013 | 0,438 |
| EINKO9 | 0,194 | 0,181 | 0,033 | , | 0,013 | 0,013 | 0,817 |
| EINKO10 | 0,226 | 0,232 | -0,015 | , | 0,007 | 0,007 | 0,725 |
| PKWHH | 0,548 | 0,671 | -0,182 | 1,345 | 0,029 | 0,161 | 0,678 |
| SEX1 | 0,613 | 0,607 | 0,013 | , | 0,007 | 0,007 | 0,940 |
| SEX2 | 0,387 | 0,394 | -0,013 | , | 0,007 | 0,007 | 0,940 |
| ALTER1 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| ALTER2 | 0,032 | 0,039 | -0,037 | , | 0,007 | 0,007 | 0,402 |
| ALTER3 | 0,323 | 0,258 | 0,138 | , | 0,065 | 0,065 | 0,801 |
| ALTER4 | 0,290 | 0,258 | 0,071 | , | 0,032 | 0,032 | 0,952 |
| ALTER5 | 0,226 | 0,297 | -0,170 | , | 0,071 | 0,071 | 0,880 |
| ALTER6 | 0,097 | 0,116 | -0,066 | , | 0,019 | 0,019 | 0,502 |
| ALTER7 | 0,032 | 0,032 | 0,000 | , | 0,000 | 0,000 | 0,065 |
| SCHULAB1 | 0,161 | 0,187 | -0,070 | , | 0,026 | 0,026 | 0,807 |
| SCHULAB2 | 0,839 | 0,813 | 0,070 | , | 0,026 | 0,026 | 0,807 |
| SCHULAB3 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| BERUF1 | 0,613 | 0,619 | -0,013 | , | 0,007 | 0,007 | 0,782 |
| BERUF2 | 0,226 | 0,194 | 0,077 | , | 0,032 | 0,032 | 0,725 |
| BERUF3 | 0,065 | 0,058 | 0,026 | , | 0,007 | 0,007 | 0,499 |
| BERUF4 | 0,097 | 0,129 | -0,109 | , | 0,032 | 0,032 | 0,589 |
| FSPKW0 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| FSPKW1 | 1,000 | 1,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| P,T,card0 | 0,226 | 0,316 | -0,216 | , | 0,090 | 0,090 | 0,741 |
| P,T,card1 | 0,774 | 0,684 | 0,216 | , | 0,090 | 0,090 | 0,741 |

**Table A. C–18**

Percent balance improvement (2017)

| Covariate | Std. Mean Diff | Var. Ratio | eCDF Mean | eCDF Max |
|---|---|---|---|---|
| distance | 61,4 | 65,7 | 96,5 | 62,1 |
| RAUMTYP1 | 95,7 | , | 95,7 | 95,7 |
| RAUMTYP2 | 81,5 | , | 81,5 | 81,5 |
| RAUMTYP3 | 92,5 | , | 92,5 | 92,5 |
| RAUMTYP4 | 100 | , | 100 | 100 |
| RAUMTYP5 | 100 | , | 100 | 100 |
| HHGRO | 75,5 | 61,9 | 56 | 49,1 |
| P0_10 | 77,2 | 94,3 | 77,2 | 68,2 |
| EINKO1 | 100 | , | 100 | 100 |
| EINKO2 | 42,7 | , | 42,7 | 42,7 |
| EINKO3 | 100 | , | 100 | 100 |
| EINKO4 | 84,1 | , | 84,1 | 84,1 |
| EINKO5 | 100 | , | 100 | 100 |
| EINKO6 | -76,9 | , | -76,9 | -76,9 |
| EINKO7 | 0,8 | , | 0,8 | 0,8 |
| EINKO8 | 81,6 | , | 81,6 | 81,6 |
| EINKO9 | 80,6 | , | 80,6 | 80,6 |
| EINKO10 | 94,2 | , | 94,2 | 94,2 |
| PKWHH | 83,6 | 40,9 | 73,2 | 59,7 |
| SEX1 | 94 | , | 94 | 94 |
| SEX2 | 94 | , | 94 | 94 |
| ALTER1 | 100 | , | 100 | 100 |
| ALTER2 | 20,2 | , | 20,2 | 20,2 |
| ALTER3 | 73,7 | , | 73,7 | 73,7 |
| ALTER4 | 67 | , | 67 | 67 |
| ALTER5 | -12,9 | , | -12,9 | -12,9 |
| ALTER6 | 84,8 | , | 84,8 | 84,8 |
| ALTER7 | 100 | , | 100 | 100 |
| SCHULAB1 | 92,4 | , | 92,4 | 92,4 |
| SCHULAB2 | 92,5 | , | 92,5 | 92,5 |
| SCHULAB3 | 100 | , | 100 | 100 |
| BERUF1 | 96,8 | , | 96,8 | 96,8 |
| BERUF2 | 4,6 | , | 4,6 | 4,6 |
| BERUF3 | 81,5 | , | 81,5 | 81,5 |
| BERUF4 | 88,2 | , | 88,2 | 88,2 |
| FSPKW0 | 100 | , | 100 | 100 |
| FSPKW1 | 100 | , | 100 | 100 |
| P,T,card0 | 82 | , | 82 | 82 |
| P,T,card1 | 82 | , | 82 | 82 |

**Table A. C–19**

Summary of balance for all data (2019)

| Covariate | Means Treated | Means Control | Std. Mean Diff | Var. Ratio | eCDF Mean | eCDF Max |
|---|---|---|---|---|---|---|
| distance | 0,276 | 0,020 | 1,377 | 9,128 | 0,496 | 0,796 |
| RAUMTYP1 | 0,925 | 0,433 | 1,866 | , | 0,492 | 0,492 |
| RAUMTYP2 | 0,000 | 0,244 | -0,573 | , | 0,244 | 0,244 |
| RAUMTYP3 | 0,050 | 0,193 | -0,657 | , | 0,143 | 0,143 |
| RAUMTYP4 | 0,025 | 0,077 | -0,331 | , | 0,052 | 0,052 |
| RAUMTYP5 | 0,000 | 0,053 | -0,240 | , | 0,053 | 0,053 |
| HHGRO | 2,200 | 2,128 | 0,064 | 1,160 | 0,027 | 0,065 |
| P0_10 | 0,225 | 0,120 | 0,182 | 1,859 | 0,028 | 0,064 |
| EINKO1 | 0,000 | 0,006 | -0,076 | , | 0,006 | 0,006 |
| EINKO2 | 0,000 | 0,034 | -0,190 | , | 0,034 | 0,034 |
| EINKO3 | 0,025 | 0,077 | -0,335 | , | 0,052 | 0,052 |
| EINKO4 | 0,050 | 0,104 | -0,249 | , | 0,054 | 0,054 |
| EINKO5 | 0,100 | 0,138 | -0,127 | , | 0,038 | 0,038 |
| EINKO6 | 0,125 | 0,123 | 0,007 | , | 0,002 | 0,002 |
| EINKO7 | 0,150 | 0,104 | 0,130 | , | 0,047 | 0,047 |
| EINKO8 | 0,125 | 0,105 | 0,061 | , | 0,020 | 0,020 |
| EINKO9 | 0,125 | 0,150 | -0,075 | , | 0,025 | 0,025 |
| EINKO10 | 0,300 | 0,160 | 0,305 | , | 0,140 | 0,140 |
| PKWHH | 0,550 | 1,346 | -1,115 | 0,710 | 0,114 | 0,436 |
| SEX1 | 0,675 | 0,499 | 0,376 | , | 0,176 | 0,176 |
| SEX2 | 0,325 | 0,501 | -0,376 | , | 0,176 | 0,176 |
| ALTER1 | 0,000 | 0,004 | -0,060 | , | 0,004 | 0,004 |
| ALTER2 | 0,025 | 0,030 | -0,030 | , | 0,005 | 0,005 |
| ALTER3 | 0,225 | 0,068 | 0,377 | , | 0,157 | 0,157 |
| ALTER4 | 0,300 | 0,176 | 0,271 | , | 0,124 | 0,124 |
| ALTER5 | 0,275 | 0,257 | 0,041 | , | 0,018 | 0,018 |
| ALTER6 | 0,175 | 0,262 | -0,230 | , | 0,087 | 0,087 |
| ALTER7 | 0,000 | 0,204 | -0,512 | , | 0,204 | 0,204 |
| SCHULAB1 | 0,100 | 0,471 | -1,236 | , | 0,371 | 0,371 |
| SCHULAB2 | 0,900 | 0,523 | 1,256 | , | 0,377 | 0,377 |
| SCHULAB3 | 0,000 | 0,006 | -0,080 | , | 0,006 | 0,006 |
| BERUF1 | 0,700 | 0,375 | 0,708 | , | 0,325 | 0,325 |
| BERUF2 | 0,125 | 0,190 | -0,196 | , | 0,065 | 0,065 |
| BERUF3 | 0,075 | 0,034 | 0,156 | , | 0,041 | 0,041 |
| BERUF4 | 0,100 | 0,401 | -1,003 | , | 0,301 | 0,301 |
| FSPKW0 | 0,000 | 0,035 | -0,194 | , | 0,035 | 0,035 |
| FSPKW1 | 1,000 | 0,965 | 0,194 | , | 0,035 | 0,035 |
| P,T,card0 | 0,075 | 0,738 | -2,516 | , | 0,663 | 0,663 |
| P,T,card1 | 0,925 | 0,262 | 2,516 | , | 0,663 | 0,663 |

**Table A. C–20**

Summary of balance for matched data (2019)

| Covariate | Means Treated | Means Control | Std. Mean Diff | Var. Ratio | eCDF Mean | eCDF Max | Std. Pair Dist. |
|---|---|---|---|---|---|---|---|
| distance | 0,276 | 0,128 | 0,799 | 2,492 | 0,045 | 0,465 | 0,802 |
| RAUMTYP1 | 0,925 | 0,855 | 0,266 | , | 0,070 | 0,070 | 0,645 |
| RAUMTYP2 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| RAUMTYP3 | 0,050 | 0,125 | -0,344 | , | 0,075 | 0,075 | 0,619 |
| RAUMTYP4 | 0,025 | 0,020 | 0,032 | , | 0,005 | 0,005 | 0,288 |
| RAUMTYP5 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| HHGRO | 2,200 | 2,190 | 0,009 | 0,936 | 0,016 | 0,035 | 1,038 |
| P0_10 | 0,225 | 0,215 | 0,017 | 1,007 | 0,010 | 0,025 | 0,659 |
| EINKO1 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| EINKO2 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| EINKO3 | 0,025 | 0,060 | -0,224 | , | 0,035 | 0,035 | 0,544 |
| EINKO4 | 0,050 | 0,070 | -0,092 | , | 0,020 | 0,020 | 0,505 |
| EINKO5 | 0,100 | 0,100 | 0,000 | , | 0,000 | 0,000 | 0,160 |
| EINKO6 | 0,125 | 0,120 | 0,015 | , | 0,005 | 0,005 | 0,650 |
| EINKO7 | 0,150 | 0,120 | 0,084 | , | 0,030 | 0,030 | 0,644 |
| EINKO8 | 0,125 | 0,110 | 0,045 | , | 0,015 | 0,015 | 0,590 |
| EINKO9 | 0,125 | 0,160 | -0,106 | , | 0,035 | 0,035 | 0,680 |
| EINKO10 | 0,300 | 0,260 | 0,087 | , | 0,040 | 0,040 | 0,851 |
| PKWHH | 0,550 | 0,860 | -0,434 | 1,268 | 0,050 | 0,275 | 0,840 |
| SEX1 | 0,675 | 0,525 | 0,320 | , | 0,150 | 0,150 | 1,004 |
| SEX2 | 0,325 | 0,475 | -0,320 | , | 0,150 | 0,150 | 1,004 |
| ALTER1 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| ALTER2 | 0,025 | 0,035 | -0,064 | , | 0,010 | 0,010 | 0,384 |
| ALTER3 | 0,225 | 0,115 | 0,263 | , | 0,110 | 0,110 | 0,647 |
| ALTER4 | 0,300 | 0,305 | -0,011 | , | 0,005 | 0,005 | 0,993 |
| ALTER5 | 0,275 | 0,290 | -0,034 | , | 0,015 | 0,015 | 0,952 |
| ALTER6 | 0,175 | 0,255 | -0,211 | , | 0,080 | 0,080 | 0,869 |
| ALTER7 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| SCHULAB1 | 0,100 | 0,205 | -0,350 | , | 0,105 | 0,105 | 0,783 |
| SCHULAB2 | 0,900 | 0,795 | 0,350 | , | 0,105 | 0,105 | 0,783 |
| SCHULAB3 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| BERUF1 | 0,700 | 0,630 | 0,153 | , | 0,070 | 0,070 | 0,829 |
| BERUF2 | 0,125 | 0,150 | -0,076 | , | 0,025 | 0,025 | 0,711 |
| BERUF3 | 0,075 | 0,055 | 0,076 | , | 0,020 | 0,020 | 0,418 |
| BERUF4 | 0,100 | 0,165 | -0,217 | , | 0,065 | 0,065 | 0,717 |
| FSPKW0 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| FSPKW1 | 1,000 | 1,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| P,T,card0 | 0,075 | 0,140 | -0,247 | , | 0,065 | 0,065 | 0,247 |
| P,T,card1 | 0,925 | 0,860 | 0,247 | , | 0,065 | 0,065 | 0,247 |

**Table A. C–21**
Percent balance improvement (2019)

| Covariate | Std. Mean Diff | Var. Ratio | eCDF Mean | eCDF Max |
|---|---|---|---|---|
| distance | 42 | 58,7 | 90,9 | 41,6 |
| RAUMTYP1 | 85,8 | , | 85,8 | 85,8 |
| RAUMTYP2 | 100 | , | 100 | 100 |
| RAUMTYP3 | 47,6 | , | 47,6 | 47,6 |
| RAUMTYP4 | 90,3 | , | 90,3 | 90,3 |
| RAUMTYP5 | 100 | , | 100 | 100 |
| HHGRO | 86,2 | 55,3 | 40,3 | 46 |
| P0_10 | 90,5 | 98,9 | 63,8 | 60,8 |
| EINKO1 | 100 | , | 100 | 100 |
| EINKO2 | 100 | , | 100 | 100 |
| EINKO3 | 33,1 | , | 33,1 | 33,1 |
| EINKO4 | 63,1 | , | 63,1 | 63,1 |
| EINKO5 | 100 | , | 100 | 100 |
| EINKO6 | -131,8 | , | -131,8 | -131,8 |
| EINKO7 | 35,5 | , | 35,5 | 35,5 |
| EINKO8 | 25,4 | , | 25,4 | 25,4 |
| EINKO9 | -41,4 | , | -41,4 | -41,4 |
| EINKO10 | 71,4 | , | 71,4 | 71,4 |
| PKWHH | 61,1 | 30,6 | 56,1 | 36,9 |
| SEX1 | 14,8 | , | 14,8 | 14,8 |
| SEX2 | 14,8 | , | 14,8 | 14,8 |
| ALTER1 | 100 | , | 100 | 100 |
| ALTER2 | -113,9 | , | -113,9 | -113,9 |
| ALTER3 | 30,1 | , | 30,1 | 30,1 |
| ALTER4 | 96 | , | 96 | 96 |
| ALTER5 | 17,9 | , | 17,9 | 17,9 |
| ALTER6 | 8,3 | , | 8,3 | 8,3 |
| ALTER7 | 100 | , | 100 | 100 |
| SCHULAB1 | 71,7 | , | 71,7 | 71,7 |
| SCHULAB2 | 72,1 | , | 72,1 | 72,1 |
| SCHULAB3 | 100 | , | 100 | 100 |
| BERUF1 | 78,4 | , | 78,4 | 78,4 |
| BERUF2 | 61,4 | , | 61,4 | 61,4 |
| BERUF3 | 51,4 | , | 51,4 | 51,4 |
| BERUF4 | 78,4 | , | 78,4 | 78,4 |
| FSPKW0 | 100 | , | 100 | 100 |
| FSPKW1 | 100 | , | 100 | 100 |
| P,T,card0 | 90,2 | , | 90,2 | 90,2 |
| P,T,card1 | 90,2 | , | 90,2 | 90,2 |

**Table A. C–22**
Summary of balance for all data (2020)

| Covariate | Means Treated | Means Control | Std. Mean Diff | Var. Ratio | eCDF Mean | eCDF Max |
|---|---|---|---|---|---|---|
| distance | 0,379 | 0,018 | 1,316 | 17,172 | 0,613 | 0,828 |
| RAUMTYP1 | 0,963 | 0,419 | 2,878 | , | 0,544 | 0,544 |
| RAUMTYP2 | 0,000 | 0,242 | -0,571 | , | 0,242 | 0,242 |
| RAUMTYP3 | 0,000 | 0,196 | -0,500 | , | 0,196 | 0,196 |
| RAUMTYP4 | 0,037 | 0,078 | -0,216 | , | 0,041 | 0,041 |
| RAUMTYP5 | 0,000 | 0,064 | -0,265 | , | 0,064 | 0,064 |
| HHGRO | 2,148 | 2,086 | 0,047 | 1,668 | 0,051 | 0,097 |
| P0_10 | 0,259 | 0,112 | 0,248 | 2,158 | 0,038 | 0,103 |
| EINKO1 | 0,000 | 0,009 | -0,094 | , | 0,009 | 0,009 |
| EINKO2 | 0,000 | 0,027 | -0,168 | , | 0,027 | 0,027 |
| EINKO3 | 0,037 | 0,067 | -0,160 | , | 0,030 | 0,030 |
| EINKO4 | 0,074 | 0,094 | -0,076 | , | 0,020 | 0,020 |
| EINKO5 | 0,111 | 0,146 | -0,112 | , | 0,035 | 0,035 |
| EINKO6 | 0,074 | 0,116 | -0,161 | , | 0,042 | 0,042 |
| EINKO7 | 0,222 | 0,090 | 0,319 | , | 0,133 | 0,133 |
| EINKO8 | 0,074 | 0,116 | -0,161 | , | 0,042 | 0,042 |
| EINKO9 | 0,037 | 0,142 | -0,556 | , | 0,105 | 0,105 |
| EINKO10 | 0,370 | 0,193 | 0,367 | , | 0,177 | 0,177 |
| PKWHH | 0,407 | 1,348 | -1,355 | 0,748 | 0,157 | 0,598 |
| SEX1 | 0,704 | 0,506 | 0,433 | , | 0,198 | 0,198 |
| SEX2 | 0,296 | 0,494 | -0,433 | , | 0,198 | 0,198 |
| ALTER1 | 0,000 | 0,002 | -0,047 | , | 0,002 | 0,002 |
| ALTER2 | 0,037 | 0,018 | 0,100 | , | 0,019 | 0,019 |
| ALTER3 | 0,222 | 0,063 | 0,383 | , | 0,159 | 0,159 |
| ALTER4 | 0,407 | 0,172 | 0,480 | , | 0,236 | 0,236 |
| ALTER5 | 0,111 | 0,246 | -0,428 | , | 0,134 | 0,134 |
| ALTER6 | 0,185 | 0,267 | -0,210 | , | 0,082 | 0,082 |
| ALTER7 | 0,037 | 0,233 | -1,036 | , | 0,196 | 0,196 |
| SCHULAB1 | 0,074 | 0,453 | -1,445 | , | 0,378 | 0,378 |
| SCHULAB2 | 0,926 | 0,541 | 1,470 | , | 0,385 | 0,385 |
| SCHULAB3 | 0,000 | 0,006 | -0,081 | , | 0,006 | 0,006 |
| BERUF1 | 0,630 | 0,362 | 0,555 | , | 0,268 | 0,268 |
| BERUF2 | 0,222 | 0,199 | 0,057 | , | 0,024 | 0,024 |
| BERUF3 | 0,037 | 0,022 | 0,077 | , | 0,015 | 0,015 |
| BERUF4 | 0,111 | 0,417 | -0,974 | , | 0,306 | 0,306 |
| FSPKW0 | 0,000 | 0,031 | -0,181 | , | 0,031 | 0,031 |
| FSPKW1 | 1,000 | 0,969 | 0,181 | , | 0,031 | 0,031 |
| P,T,card0 | 0,148 | 0,759 | -1,719 | , | 0,611 | 0,611 |
| P,T,card1 | 0,852 | 0,241 | 1,719 | , | 0,611 | 0,611 |

**Table A. C–23**
Summary of balance for matched data (2020)

| Covariate | Means Treated | Means Control | Std. Mean Diff | Var. Ratio | eCDF Mean | eCDF Max | Std. Pair Dist. |
|---|---|---|---|---|---|---|---|
| distance | 0,379 | 0,114 | 0,966 | 3,828 | 0,079 | 0,585 | 0,967 |
| RAUMTYP1 | 0,963 | 0,933 | 0,157 | , | 0,030 | 0,030 | 0,549 |
| RAUMTYP2 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| RAUMTYP3 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| RAUMTYP4 | 0,037 | 0,067 | -0,157 | , | 0,030 | 0,030 | 0,549 |
| RAUMTYP5 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| HHGRO | 2,148 | 2,096 | 0,039 | 1,347 | 0,028 | 0,052 | 0,914 |
| P0_10 | 0,259 | 0,230 | 0,050 | 0,989 | 0,011 | 0,037 | 0,598 |
| EINKO1 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| EINKO2 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| EINKO3 | 0,037 | 0,037 | 0,000 | , | 0,000 | 0,000 | 0,059 |
| EINKO4 | 0,074 | 0,111 | -0,141 | , | 0,037 | 0,037 | 0,594 |
| EINKO5 | 0,111 | 0,141 | -0,094 | , | 0,030 | 0,030 | 0,660 |
| EINKO6 | 0,074 | 0,119 | -0,170 | , | 0,044 | 0,044 | 0,622 |
| EINKO7 | 0,222 | 0,126 | 0,232 | , | 0,096 | 0,096 | 0,695 |
| EINKO8 | 0,074 | 0,111 | -0,141 | , | 0,037 | 0,037 | 0,707 |
| EINKO9 | 0,037 | 0,059 | -0,118 | , | 0,022 | 0,022 | 0,510 |
| EINKO10 | 0,370 | 0,296 | 0,153 | , | 0,074 | 0,074 | 0,828 |
| PKWHH | 0,407 | 0,785 | -0,544 | 1,323 | 0,068 | 0,393 | 0,950 |
| SEX1 | 0,704 | 0,585 | 0,260 | , | 0,119 | 0,119 | 0,941 |
| SEX2 | 0,296 | 0,415 | -0,260 | , | 0,119 | 0,119 | 0,941 |
| ALTER1 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| ALTER2 | 0,037 | 0,015 | 0,118 | , | 0,022 | 0,022 | 0,275 |
| ALTER3 | 0,222 | 0,096 | 0,303 | , | 0,126 | 0,126 | 0,659 |
| ALTER4 | 0,407 | 0,319 | 0,181 | , | 0,089 | 0,089 | 0,844 |
| ALTER5 | 0,111 | 0,200 | -0,283 | , | 0,089 | 0,089 | 0,849 |
| ALTER6 | 0,185 | 0,274 | -0,229 | , | 0,089 | 0,089 | 0,915 |
| ALTER7 | 0,037 | 0,096 | -0,314 | , | 0,059 | 0,059 | 0,628 |
| SCHULAB1 | 0,074 | 0,185 | -0,424 | , | 0,111 | 0,111 | 0,707 |
| SCHULAB2 | 0,926 | 0,815 | 0,424 | , | 0,111 | 0,111 | 0,707 |
| SCHULAB3 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| BERUF1 | 0,630 | 0,519 | 0,230 | , | 0,111 | 0,111 | 0,936 |
| BERUF2 | 0,222 | 0,267 | -0,107 | , | 0,044 | 0,044 | 0,784 |
| BERUF3 | 0,037 | 0,015 | 0,118 | , | 0,022 | 0,022 | 0,275 |
| BERUF4 | 0,111 | 0,200 | -0,283 | , | 0,089 | 0,089 | 0,849 |
| FSPKW0 | 0,000 | 0,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| FSPKW1 | 1,000 | 1,000 | 0,000 | , | 0,000 | 0,000 | 0,000 |
| P,T,card0 | 0,148 | 0,370 | -0,626 | , | 0,222 | 0,222 | 1,001 |
| P,T,card1 | 0,852 | 0,630 | 0,626 | , | 0,222 | 0,222 | 1,001 |

**Table A. C–24**

Percent balance improvement (2020)

| Covariate | Std. Mean Diff | Var. Ratio | eCDF Mean | eCDF Max |
|---|---|---|---|---|
| distance | 26,6 | 52,8 | 87,1 | 29,3 |
| RAUMTYP1 | 94,5 | , | 94,5 | 94,5 |
| RAUMTYP2 | 100 | , | 100 | 100 |
| RAUMTYP3 | 100 | , | 100 | 100 |
| RAUMTYP4 | 27,5 | , | 27,5 | 27,5 |
| RAUMTYP5 | 100 | , | 100 | 100 |
| HHGRO | 16 | 41,8 | 44,9 | 46,5 |
| P0_10 | 79,9 | 98,5 | 70,7 | 64 |
| EINKO1 | 100 | , | 100 | 100 |
| EINKO2 | 100 | , | 100 | 100 |
| EINKO3 | 100 | , | 100 | 100 |
| EINKO4 | -86,7 | , | -86,7 | -86,7 |
| EINKO5 | 15,6 | , | 15,6 | 15,6 |
| EINKO6 | -5,2 | , | -5,2 | -5,2 |
| EINKO7 | 27,4 | , | 27,4 | 27,4 |
| EINKO8 | 12,3 | , | 12,3 | 12,3 |
| EINKO9 | 78,8 | , | 78,8 | 78,8 |
| EINKO10 | 58,2 | , | 58,2 | 58,2 |
| PKWHH | 59,8 | 3,7 | 56,7 | 34,4 |
| SEX1 | 40,1 | , | 40,1 | 40,1 |
| SEX2 | 40,1 | , | 40,1 | 40,1 |
| ALTER1 | 100 | , | 100 | 100 |
| ALTER2 | -17,6 | , | -17,6 | -17,6 |
| ALTER3 | 20,9 | , | 20,9 | 20,9 |
| ALTER4 | 62,3 | , | 62,3 | 62,3 |
| ALTER5 | 33,8 | , | 33,8 | 33,8 |
| ALTER6 | -8,9 | , | -8,9 | -8,9 |
| ALTER7 | 69,7 | , | 69,7 | 69,7 |
| SCHULAB1 | 70,6 | , | 70,6 | 70,6 |
| SCHULAB2 | 71,1 | , | 71,1 | 71,1 |
| SCHULAB3 | 100 | , | 100 | 100 |
| BERUF1 | 58,5 | , | 58,5 | 58,5 |
| BERUF2 | -87,4 | , | -87,4 | -87,4 |
| BERUF3 | -51,9 | , | -51,9 | -51,9 |
| BERUF4 | 71 | , | 71 | 71 |
| FSPKW0 | 100 | , | 100 | 100 |
| FSPKW1 | 100 | , | 100 | 100 |
| P,T,card0 | 63,6 | , | 63,6 | 63,6 |
| P,T,card1 | 63,6 | , | 63,6 | 63,6 |

# Appendix D
# Car ownership level of the matched IDs over time

The outcome of the matching method was 676 matched IDs called final control units. As it can be seen in **Table A. D–1**, all the IDs are listed with their car ownership levels in three potential years. As expected, only two years of information were provided for some IDs since one of the rules to select a control unit was defined as having more than one year of information.

**Table A. D–1**
Car ownership level of all the final control group units

| # | ID_der | PKWHH | | |
|---|---|---|---|---|
| | | First year | Second year | Third year |
| 1 | 370671_1 | 1 | 1 | 1 |
| 2 | 350808_1 | 1 | 1 | - |
| 3 | 3910001258_1 | 1 | 1 | 1 |
| 4 | 370142_1 | 1 | 1 | 1 |
| 5 | 370155_1 | 1 | 1 | 1 |
| 6 | 4101001433_2 | 1 | 1 | 1 |
| 7 | 3900000893_1 | 1 | 1 | 1 |
| 8 | 350232_1 | 0 | 0 | - |
| 9 | 350262_1 | 1 | 1 | - |
| 10 | 4118000743_1 | 1 | 1 | 1 |
| 11 | 4101002059_1 | 1 | 1 | 1 |
| 12 | 4101002709_1 | 0 | 0 | 0 |
| 13 | 7910003095_1 | 0 | 0 | 0 |
| 14 | 7910001250_1 | 0 | 0 | 0 |
| 15 | 3900000913_1 | 1 | 1 | 1 |
| 16 | 350341_1 | 1 | 1 | - |
| 17 | 3900000395_1 | 1 | 1 | 1 |
| 18 | 350729_1 | 1 | 1 | - |
| 19 | 370202_1 | 1 | 1 | - |
| 20 | 7900002567_1 | 0 | 0 | - |
| 21 | 7900000869_1 | 1 | 1 | - |
| 22 | 7910001183_1 | 1 | 1 | 1 |
| 23 | 370060_2 | 1 | 1 | 1 |
| 24 | 350474_1 | 1 | 1 | - |
| 25 | 370298_1 | 0 | 0 | - |
| 26 | 370365_1 | 0 | 0 | - |
| 27 | 3900000860_1 | 0 | 0 | 0 |
| 28 | 370724_1 | 1 | 1 | 1 |
| 29 | 350072_1 | 1 | 1 | - |
| 30 | 4101004005_3 | 1 | 1 | 1 |
| 31 | 7910000282_1 | 1 | 1 | 1 |

| # | ID_der | PKWHH | | |
|---|---|---|---|---|
| | | First year | Second year | Third year |
| 32 | 4111000388_1 | 0 | 0 | 0 |
| 33 | 3910000189_2 | 1 | 1 | 1 |
| 34 | 4301012636_1 | 0 | 0 | 0 |
| 35 | 4101001708_1 | 0 | 0 | - |
| 36 | 8301013667_1 | 0 | 0 | 0 |
| 37 | 4301013166_2 | 1 | 1 | 1 |
| 38 | 4118001099_1 | 1 | 1 | - |
| 39 | 8101002430_2 | 1 | 1 | 1 |
| 40 | 350543_1 | 0 | 0 | - |
| 41 | 7910001363_1 | 1 | 1 | 1 |
| 42 | 8101002542_1 | 0 | 0 | - |
| 43 | 3900002475_1 | 1 | 1 | - |
| 44 | 8101002570_1 | 1 | 1 | 1 |
| 45 | 7900001056_1 | 0 | 0 | 0 |
| 46 | 4101000951_1 | 0 | 0 | - |
| 47 | 350343_1 | 0 | 0 | - |
| 48 | 750038_1 | 1 | 1 | - |
| 49 | 3900000995_1 | 0 | 0 | 0 |
| 50 | 3910001452_1 | 0 | 0 | - |
| 51 | 7910001371_1 | 0 | 0 | 0 |
| 52 | 370192_1 | 1 | 1 | 1 |
| 53 | 3900002598_1 | 1 | 1 | 1 |
| 54 | 350797_1 | 1 | 1 | - |
| 55 | 770038_1 | 0 | 0 | 0 |
| 56 | 750001_1 | 0 | 0 | - |
| 57 | 3900000561_1 | 0 | 0 | 1 |
| 58 | 370354_1 | 1 | 1 | - |
| 59 | 7900000506_2 | 1 | 1 | 1 |
| 60 | 7910000030_1 | 0 | 0 | 0 |
| 61 | 3900000406_1 | 1 | 1 | - |
| 62 | 4101003460_1 | 0 | 0 | 0 |
| 63 | 350091_1 | 0 | 0 | - |
| 64 | 370014_3 | 1 | 1 | - |
| 65 | 370661_1 | 1 | 1 | 1 |
| 66 | 370584_3 | 0 | 0 | - |
| 67 | 370718_1 | 0 | 0 | 0 |
| 68 | 4111000263_1 | 1 | 1 | 1 |
| 69 | 770173_1 | 0 | 0 | - |
| 70 | 4101004877_1 | 1 | 1 | - |
| 71 | 4118001003_1 | 1 | 1 | 1 |
| 72 | 3900001154_1 | 1 | 1 | - |
| 73 | 3910000234_1 | 1 | 1 | - |

| # | ID_der | PKWHH | | |
|---|---|---|---|---|
| | | First year | Second year | Third year |
| 74 | 7900000674_1 | 1 | 1 | 1 |
| 75 | 8118000329_2 | 1 | 1 | 1 |
| 76 | 370374_2 | 1 | 1 | 1 |
| 77 | 3910001256_1 | 1 | 1 | 1 |
| 78 | 7900002366_1 | 0 | 0 | 0 |
| 79 | 7910001191_2 | 0 | 0 | 0 |
| 80 | 350655_2 | 1 | 1 | - |
| 81 | 7910000139_1 | 1 | 1 | 1 |
| 82 | 350015_2 | 1 | 1 | - |
| 83 | 4101004572_1 | 1 | 1 | 1 |
| 84 | 4118000941_1 | 0 | 0 | 0 |
| 85 | 3900002565_2 | 1 | 1 | - |
| 86 | 3900002599_1 | 1 | 1 | 1 |
| 87 | 350093_1 | 1 | 1 | - |
| 88 | 7910000243_1 | 1 | 1 | 1 |
| 89 | 370563_1 | 1 | 1 | 1 |
| 90 | 4101001709_1 | 1 | 1 | 1 |
| 91 | 3910001468_1 | 1 | 1 | 0 |
| 92 | 350406_1 | 2 | 2 | - |
| 93 | 3910002996_1 | 0 | 0 | 0 |
| 94 | 3910001372_1 | 0 | 0 | 1 |
| 95 | 7900000559_1 | 0 | 0 | 0 |
| 96 | 8118000634_1 | 0 | 0 | 0 |
| 97 | 4101001698_1 | 1 | 1 | - |
| 98 | 4111003121_2 | 1 | 1 | - |
| 99 | 8301013664_1 | 1 | 1 | 1 |
| 100 | 3900002608_1 | 4 | 1 | 0 |
| 101 | 3900000981_1 | 2 | 2 | 1 |
| 102 | 4301012669_1 | 0 | 0 | 0 |
| 103 | 4311010777_1 | 0 | 0 | 0 |
| 104 | 4311010004_2 | 1 | 1 | 1 |
| 105 | 4101000004_1 | 0 | 0 | 0 |
| 106 | 4301014006_1 | 1 | 1 | 1 |
| 107 | 8311010926_2 | 0 | 0 | 0 |
| 108 | 4301012974_1 | 1 | 1 | 2 |
| 109 | 4511021953_3 | 1 | 1 | - |
| 110 | 3910000223_1 | 1 | 1 | 1 |
| 111 | 4101001824_1 | 1 | 1 | 1 |
| 112 | 350300_1 | 1 | 1 | - |
| 113 | 350807_2 | 1 | 1 | - |
| 114 | 3910001474_1 | 1 | 1 | 1 |
| 115 | 350651_2 | 1 | 1 | - |

| # | ID_der | PKWHH | | |
|---|---|---|---|---|
| | | First year | Second year | Third year |
| 116 | 370473_1 | 1 | 1 | 1 |
| 117 | 7910001333_2 | 0 | 0 | 0 |
| 118 | 3910001317_1 | 1 | 1 | 1 |
| 119 | 3900002451_1 | 1 | 1 | 1 |
| 120 | 4111004415_1 | 0 | 0 | - |
| 121 | 4118000346_1 | 0 | 1 | 1 |
| 122 | 7910001481_1 | 0 | 0 | 0 |
| 123 | 3900001026_1 | 1 | 1 | - |
| 124 | 3900002558_1 | 1 | 1 | - |
| 125 | 3900000476_1 | 1 | 1 | 1 |
| 126 | 3900002552_1 | 1 | 1 | 1 |
| 127 | 3900001137_1 | 1 | 1 | - |
| 128 | 370403_1 | 0 | 0 | - |
| 129 | 7910002939_1 | 0 | 0 | - |
| 130 | 4101003934_1 | 0 | 0 | 0 |
| 131 | 3910000170_1 | 1 | 1 | 1 |
| 132 | 3910001483_1 | 0 | 0 | - |
| 133 | 3900000932_1 | 0 | 0 | - |
| 134 | 4111000203_1 | 1 | 1 | 1 |
| 135 | 3910003089_1 | 0 | 0 | - |
| 136 | 370072_1 | 1 | 1 | 1 |
| 137 | 370757_1 | 0 | 0 | 1 |
| 138 | 7900000966_1 | 0 | 0 | 1 |
| 139 | 7910001445_1 | 0 | 0 | - |
| 140 | 370316_1 | 0 | 0 | - |
| 141 | 370119_1 | 0 | 0 | 0 |
| 142 | 770076_1 | 1 | 1 | 1 |
| 143 | 3900002385_1 | 0 | 0 | 0 |
| 144 | 370085_1 | 0 | 0 | - |
| 145 | 350322_1 | 0 | 0 | - |
| 146 | 370425_1 | 2 | 2 | 2 |
| 147 | 750131_1 | 1 | 1 | - |
| 148 | 3910002955_1 | 0 | 0 | - |
| 149 | 3900001107_1 | 1 | 1 | - |
| 150 | 3910000084_1 | 1 | 1 | 2 |
| 151 | 3910001172_1 | 1 | 1 | 1 |
| 152 | 350555_1 | 0 | 0 | - |
| 153 | 7910003109_1 | 0 | 0 | - |
| 154 | 3900000417_1 | 2 | 1 | 1 |
| 155 | 3900000428_2 | 1 | 1 | - |
| 156 | 7900000899_2 | 1 | 1 | - |
| 157 | 4101000867_1 | 0 | 0 | 0 |

| # | ID_der | PKWHH | | |
|---|---|---|---|---|
| | | First year | Second year | Third year |
| 158 | 4101004912_1 | 1 | 1 | - |
| 159 | 4118000751_1 | 1 | 1 | - |
| 160 | 4111003114_1 | 0 | 0 | - |
| 161 | 370080_1 | 0 | 0 | 0 |
| 162 | 3900001123_1 | 2 | 1 | - |
| 163 | 370086_2 | 1 | 1 | 1 |
| 164 | 4101001976_1 | 1 | 1 | - |
| 165 | 7910000225_1 | 1 | 1 | - |
| 166 | 4101003250_2 | 1 | 1 | 1 |
| 167 | 3910000082_1 | 1 | 1 | 1 |
| 168 | 8301012304_2 | 0 | 0 | 0 |
| 169 | 3900002434_1 | 2 | 1 | 1 |
| 170 | 4301015438_1 | 1 | 1 | 1 |
| 171 | 4301013351_1 | 1 | 1 | 1 |
| 172 | 4311010203_2 | 1 | 1 | 1 |
| 173 | 8301012060_1 | 0 | 0 | 0 |
| 174 | 3900000785_1 | 1 | 0 | 0 |
| 175 | 4301013590_1 | 1 | 1 | 1 |
| 176 | 4301011824_1 | 0 | 0 | 0 |
| 177 | 4311010201_1 | 1 | 1 | - |
| 178 | 7910001387_2 | 0 | 0 | 0 |
| 179 | 8118000510_1 | 1 | 1 | 1 |
| 180 | 8301011886_2 | 0 | 0 | 0 |
| 181 | 4311010227_1 | 0 | 0 | 0 |
| 182 | 4311010359_1 | 0 | 0 | 0 |
| 183 | 4101001275_1 | 1 | 1 | 1 |
| 184 | 7910000005_2 | 2 | 2 | 1 |
| 185 | 4311012476_1 | 0 | 0 | 0 |
| 186 | 7910000065_1 | 0 | 0 | 0 |
| 187 | 4118000102_1 | 0 | 0 | 0 |
| 188 | 8101002406_2 | 1 | 1 | - |
| 189 | 4101003605_1 | 1 | 1 | 1 |
| 190 | 8311010474_2 | 2 | 2 | - |
| 191 | 8301016171_2 | 0 | 0 | 0 |
| 192 | 4301015474_2 | 1 | 1 | 1 |
| 193 | 8101004720_1 | 0 | 0 | 0 |
| 194 | 4311011104_1 | 1 | 1 | 1 |
| 195 | 4118001030_1 | 2 | 2 | - |
| 196 | 4111000096_1 | 2 | 1 | - |
| 197 | 8111004358_1 | 1 | 1 | 1 |
| 198 | 8501023674_1 | 0 | 0 | - |
| 199 | 4101003497_1 | 0 | 0 | 0 |

| # | ID_der | PKWHH | | |
|---|---|---|---|---|
| | | First year | Second year | Third year |
| 200 | 4501025014_2 | 1 | 1 | 1 |
| 201 | 4501024494_1 | 0 | 0 | 0 |
| 202 | 4501024881_2 | 1 | 1 | 1 |
| 203 | 8501022402_1 | 1 | 1 | 1 |
| 204 | 8511020672_1 | 1 | 2 | 2 |
| 205 | 8101003861_1 | 0 | 0 | 0 |
| 206 | 4511020300_1 | 0 | 0 | 0 |
| 207 | 4511020887_2 | 1 | 1 | - |
| 208 | 4511020520_1 | 0 | 0 | 0 |
| 209 | 4101003743_1 | 1 | 1 | 1 |
| 210 | 4111003110_1 | 0 | 0 | 0 |
| 211 | 4311010870_1 | 1 | 1 | 1 |
| 212 | 4511020833_1 | 1 | 1 | 1 |
| 213 | 4511021372_1 | 0 | 1 | 1 |
| 214 | 8501025175_1 | 1 | 1 | 1 |
| 215 | 4111000474_2 | 2 | 1 | 1 |
| 216 | 4311010031_1 | 1 | 1 | - |
| 217 | 4501024916_1 | 0 | 0 | 0 |
| 218 | 4101001968_1 | 1 | 1 | 1 |
| 219 | 4511021886_1 | 1 | 1 | 1 |
| 220 | 4301014173_1 | 0 | 0 | 0 |
| 221 | 4311011471_1 | 0 | 0 | - |
| 222 | 4511021417_1 | 0 | 0 | 1 |
| 223 | 8311013783_1 | 0 | 0 | 0 |
| 224 | 4511020838_1 | 1 | 1 | 1 |
| 225 | 4511020457_2 | 1 | 1 | - |
| 226 | 4101003335_1 | 0 | 0 | - |
| 227 | 8101002327_1 | 1 | 1 | - |
| 228 | 8301014124_1 | 0 | 0 | 0 |
| 229 | 4301014662_1 | 0 | 0 | - |
| 230 | 4301014901_2 | 2 | 2 | - |
| 231 | 8311015369_1 | 1 | 1 | 1 |
| 232 | 4501026026_1 | 1 | 1 | - |
| 233 | 8118000737_1 | 1 | 1 | 1 |
| 234 | 8501024289_2 | 1 | 1 | 1 |
| 235 | 8511021686_1 | 0 | 0 | 0 |
| 236 | 4501023962_1 | 0 | 0 | 0 |
| 237 | 4501024101_1 | 1 | 1 | 1 |
| 238 | 4311010337_2 | 0 | 0 | 0 |
| 239 | 4501024162_3 | 1 | 1 | 1 |
| 240 | 4501022174_1 | 1 | 1 | 2 |
| 241 | 8501022964_1 | 0 | 0 | 0 |

| # | ID_der | PKWHH | | |
|---|---|---|---|---|
| | | First year | Second year | Third year |
| 242 | 8511021898_2 | 0 | 0 | - |
| 243 | 4511021263_2 | 1 | 2 | - |
| 244 | 8511020905_2 | 1 | 1 | 1 |
| 245 | 4501022561_2 | 0 | 0 | - |
| 246 | 8511021447_1 | 1 | 1 | 1 |
| 247 | 8511021925_1 | 1 | 1 | 1 |
| 248 | 4501023131_2 | 1 | 1 | - |
| 249 | 4511020083_1 | 1 | 1 | 2 |
| 250 | 4511021706_1 | 1 | 1 | - |
| 251 | 4101001812_1 | 3 | 1 | - |
| 252 | 4301012007_1 | 0 | 0 | - |
| 253 | 4301015776_1 | 0 | 0 | 0 |
| 254 | 4501022537_1 | 1 | 1 | - |
| 255 | 4501026198_2 | 1 | 1 | 1 |
| 256 | 4501023718_2 | 0 | 0 | - |
| 257 | 4501024197_2 | 1 | 1 | - |
| 258 | 4511020693_2 | 1 | 2 | - |
| 259 | 4511022029_2 | 1 | 1 | 1 |
| 260 | 4111004410_1 | 1 | 1 | 1 |
| 261 | 4311010278_1 | 1 | 1 | 1 |
| 262 | 4511020180_1 | 0 | 0 | 0 |
| 263 | 8111000779_2 | 1 | 1 | 1 |
| 264 | 8501022670_1 | 0 | 0 | 0 |
| 265 | 4311011097_1 | 1 | 1 | - |
| 266 | 4501022341_1 | 1 | 1 | 1 |
| 267 | 4501024727_1 | 1 | 1 | 1 |
| 268 | 8311011120_1 | 1 | 1 | 1 |
| 269 | 8501024802_1 | 1 | 1 | 1 |
| 270 | 4701034075_2 | 2 | 2 | 2 |
| 271 | 4501023994_1 | 1 | 1 | 1 |
| 272 | 4501026174_1 | 1 | 1 | 1 |
| 273 | 4511021875_1 | 1 | 1 | 1 |
| 274 | 8511020870_1 | 1 | 1 | - |
| 275 | 4501024528_1 | 2 | 2 | 2 |
| 276 | 4701032279_1 | 1 | 1 | 1 |
| 277 | 4301015137_1 | 1 | 1 | - |
| 278 | 4311010726_1 | 1 | 1 | 1 |
| 279 | 8701035908_1 | 1 | 1 | 2 |
| 280 | 4701033341_2 | 2 | 2 | 2 |
| 281 | 4701035139_2 | 1 | 1 | 1 |
| 282 | 4711030261_1 | 1 | 1 | 1 |
| 283 | 4301015684_1 | 0 | 0 | 0 |

| # | ID_der | PKWHH | | |
|---|---|---|---|---|
| | | First year | Second year | Third year |
| 284 | 4701033442_1 | 0 | 0 | - |
| 285 | 4701035289_1 | 0 | 0 | - |
| 286 | 4711030238_1 | 1 | 1 | - |
| 287 | 4711031890_1 | 1 | 1 | 1 |
| 288 | 8711031509_2 | 1 | 1 | 1 |
| 289 | 8711030676_2 | 1 | 1 | 1 |
| 290 | 4501022179_1 | 0 | 0 | 0 |
| 291 | 4501023823_2 | 1 | 1 | 2 |
| 292 | 4311011403_1 | 2 | 2 | 2 |
| 293 | 4301011564_2 | 1 | 1 | 1 |
| 294 | 4711031301_1 | 1 | 1 | 1 |
| 295 | 4511020988_1 | 1 | 1 | 1 |
| 296 | 4711030230_1 | 0 | 0 | 0 |
| 297 | 8301013659_1 | 0 | 0 | - |
| 298 | 4501025911_1 | 0 | 0 | - |
| 299 | 4711030035_1 | 0 | 0 | 0 |
| 300 | 8501024589_2 | 1 | 1 | - |
| 301 | 4511021357_1 | 0 | 0 | - |
| 302 | 4711030171_1 | 0 | 0 | - |
| 303 | 4711030380_1 | 1 | 1 | 1 |
| 304 | 4701035149_2 | 2 | 2 | 2 |
| 305 | 8511021806_2 | 1 | 1 | 1 |
| 306 | 8711030837_1 | 1 | 1 | 1 |
| 307 | 4301013942_1 | 1 | 1 | 1 |
| 308 | 4711031936_1 | 1 | 1 | - |
| 309 | 4501024009_1 | 1 | 1 | 1 |
| 310 | 4501022207_1 | 1 | 1 | 1 |
| 311 | 4501024444_1 | 2 | 2 | - |
| 312 | 4711031209_1 | 1 | 1 | - |
| 313 | 4701035822_2 | 1 | 1 | 1 |
| 314 | 8701035047_1 | 0 | 1 | 1 |
| 315 | 8711031595_2 | 1 | 1 | 1 |
| 316 | 8301016144_3 | 2 | 2 | - |
| 317 | 4501025033_1 | 1 | 1 | 1 |
| 318 | 4711031982_1 | 1 | 1 | - |
| 319 | 8701034209_1 | 0 | 0 | - |
| 320 | 4701034034_2 | 1 | 1 | 1 |
| 321 | 8301011903_1 | 1 | 1 | 1 |
| 322 | 4501026075_1 | 1 | 1 | 1 |
| 323 | 4511020303_1 | 0 | 0 | - |
| 324 | 4511020684_1 | 0 | 0 | 0 |
| 325 | 4701034550_1 | 1 | 1 | 1 |

| # | ID_der | PKWHH | | |
|---|---|---|---|---|
| | | First year | Second year | Third year |
| 326 | 4501024849_1 | 1 | 1 | 1 |
| 327 | 8501023937_1 | 1 | 1 | 1 |
| 328 | 4511021201_2 | 1 | 1 | - |
| 329 | 4701032963_1 | 1 | 1 | - |
| 330 | 4711030079_1 | 1 | 1 | 1 |
| 331 | 8511020777_1 | 1 | 1 | - |
| 332 | 4711030365_1 | 0 | 0 | - |
| 333 | 4711030220_1 | 0 | 0 | - |
| 334 | 4701032643_2 | 1 | 1 | - |
| 335 | 4711030769_1 | 1 | 1 | - |
| 336 | 8701033697_2 | 1 | 1 | 1 |
| 337 | 4701035281_1 | 0 | 0 | 0 |
| 338 | 4711030855_2 | 1 | 1 | 1 |
| 339 | 4711032059_1 | 0 | 0 | 0 |
| 340 | 4511021813_1 | 1 | 1 | - |
| 341 | 4701035471_1 | 1 | 1 | 1 |
| 342 | 8711031131_1 | 1 | 1 | 1 |
| 343 | 4301013416_1 | 0 | 0 | 0 |
| 344 | 4511020035_1 | 0 | 0 | - |
| 345 | 4701034547_2 | 1 | 1 | 1 |
| 346 | 8701034211_1 | 0 | 0 | 0 |
| 347 | 4501022859_2 | 1 | 0 | - |
| 348 | 4511020779_1 | 0 | 0 | 0 |
| 349 | 4511020803_2 | 1 | 1 | - |
| 350 | 4701032627_2 | 1 | 1 | - |
| 351 | 4701033993_1 | 0 | 0 | 0 |
| 352 | 4501022776_1 | 1 | 1 | 1 |
| 353 | 4701033416_1 | 0 | 0 | 0 |
| 354 | 4701035779_1 | 1 | 1 | - |
| 355 | 8301014408_1 | 0 | 0 | 0 |
| 356 | 4311010054_1 | 4 | 2 | 1 |
| 357 | 8711031602_1 | 0 | 0 | 0 |
| 358 | 4301014481_1 | 2 | 1 | - |
| 359 | 4701033625_1 | 0 | 0 | 0 |
| 360 | 4701035816_1 | 0 | 0 | - |
| 361 | 8701033145_1 | 0 | 1 | 1 |
| 362 | 4701032377_1 | 1 | 1 | 1 |
| 363 | 4701034640_2 | 1 | 1 | 1 |
| 364 | 8501023221_1 | 0 | 0 | - |
| 365 | 4301011567_1 | 0 | 0 | - |
| 366 | 4701035664_2 | 1 | 1 | 1 |
| 367 | 8501023255_1 | 1 | 1 | 1 |

| # | ID_der | PKWHH | | |
|---|---|---|---|---|
| | | First year | Second year | Third year |
| 368 | 4501024614_2 | 1 | 1 | 1 |
| 369 | 4501024672_2 | 2 | 2 | 2 |
| 370 | 4501024777_1 | 1 | 1 | - |
| 371 | 4511021938_2 | 2 | 2 | - |
| 372 | 8501024332_1 | 0 | 0 | - |
| 373 | 4501022843_1 | 1 | 1 | 1 |
| 374 | 4511021468_1 | 2 | 1 | 1 |
| 375 | 4701033891_1 | 0 | 0 | 0 |
| 376 | 4701034644_1 | 1 | 1 | 1 |
| 377 | 4701034951_1 | 0 | 0 | - |
| 378 | 4701033047_1 | 0 | 0 | 0 |
| 379 | 4701033103_2 | 1 | 1 | 1 |
| 380 | 4701034641_1 | 0 | 0 | 0 |
| 381 | 8701032458_1 | 1 | 1 | 1 |
| 382 | 4501022292_1 | 1 | 1 | - |
| 383 | 4701034953_1 | 1 | 1 | 1 |
| 384 | 4501026006_2 | 1 | 1 | 1 |
| 385 | 4501023143_1 | 1 | 1 | 1 |
| 386 | 4901044281_2 | 1 | 1 | 1 |
| 387 | 4501022881_1 | 1 | 1 | 1 |
| 388 | 8901044846_1 | 0 | 0 | 0 |
| 389 | 8511020617_1 | 1 | 0 | - |
| 390 | 8901044463_1 | 1 | 1 | - |
| 391 | 4901044203_1 | 0 | 0 | 0 |
| 392 | 4901043548_1 | 0 | 0 | 0 |
| 393 | 4711031168_1 | 1 | 1 | 1 |
| 394 | 4901043707_1 | 1 | 1 | 1 |
| 395 | 4911041174_1 | 0 | 0 | 0 |
| 396 | 4911042073_1 | 1 | 1 | 1 |
| 397 | 4911041943_2 | 0 | 0 | - |
| 398 | 4701032330_2 | 1 | 1 | 1 |
| 399 | 4701033025_2 | 1 | 1 | 1 |
| 400 | 4711030700_2 | 1 | 1 | - |
| 401 | 4901045249_3 | 1 | 2 | 2 |
| 402 | 8911044962_1 | 0 | 0 | - |
| 403 | 4711030672_1 | 0 | 0 | - |
| 404 | 4911040571_1 | 1 | 1 | 1 |
| 405 | 4501026529_1 | 1 | 1 | 1 |
| 406 | 4901043506_1 | 1 | 1 | 1 |
| 407 | 4511020722_1 | 1 | 1 | - |
| 408 | 4711030635_1 | 1 | 1 | 2 |
| 409 | 4911040703_1 | 1 | 1 | 1 |

| # | ID_der | PKWHH | | |
|---|---|---|---|---|
| | | First year | Second year | Third year |
| 410 | 4501023516_2 | 1 | 1 | 1 |
| 411 | 4901043055_1 | 0 | 0 | - |
| 412 | 8911041476_1 | 0 | 0 | - |
| 413 | 4911040321_1 | 1 | 1 | 1 |
| 414 | 4901042988_1 | 1 | 1 | 1 |
| 415 | 4911046157_1 | 1 | 1 | 1 |
| 416 | 8901043946_2 | 1 | 1 | 1 |
| 417 | 8901042738_2 | 1 | 1 | 1 |
| 418 | 8701035227_1 | 0 | 0 | 0 |
| 419 | 4701032822_1 | 1 | 1 | - |
| 420 | 4901044246_2 | 1 | 1 | 1 |
| 421 | 4901042880_4 | 0 | 0 | 0 |
| 422 | 4901044357_1 | 1 | 1 | 1 |
| 423 | 4901044543_1 | 0 | 0 | 0 |
| 424 | 8511021253_1 | 1 | 1 | 1 |
| 425 | 4901043835_1 | 1 | 1 | 1 |
| 426 | 8901046094_1 | 1 | 2 | - |
| 427 | 4911042427_1 | 1 | 1 | - |
| 428 | 8711030669_1 | 1 | 1 | 1 |
| 429 | 8911041380_1 | 0 | 0 | 0 |
| 430 | 4901042627_1 | 0 | 0 | - |
| 431 | 4901043859_1 | 1 | 1 | 1 |
| 432 | 8511020227_1 | 1 | 1 | 1 |
| 433 | 8901043463_1 | 0 | 0 | - |
| 434 | 4901043661_1 | 0 | 0 | 0 |
| 435 | 4911040973_1 | 0 | 0 | 0 |
| 436 | 4911045370_1 | 1 | 1 | - |
| 437 | 8911042195_1 | 0 | 0 | 0 |
| 438 | 4901042984_1 | 0 | 0 | - |
| 439 | 8701033187_1 | 1 | 1 | 1 |
| 440 | 4711030820_1 | 1 | 1 | 1 |
| 441 | 4701033474_3 | 1 | 1 | - |
| 442 | 4901045145_1 | 1 | 1 | - |
| 443 | 8701032788_1 | 0 | 0 | 0 |
| 444 | 8701032772_2 | 1 | 1 | - |
| 445 | 8701033161_1 | 1 | 1 | 1 |
| 446 | 8711030490_1 | 0 | 0 | - |
| 447 | 4911040516_1 | 1 | 1 | - |
| 448 | 4911041846_1 | 1 | 1 | 1 |
| 449 | 4901043693_1 | 0 | 0 | 0 |
| 450 | 4901044120_1 | 0 | 0 | - |
| 451 | 8901043793_1 | 0 | 1 | - |

| # | ID_der | PKWHH | | |
|---|---|---|---|---|
| | | First year | Second year | Third year |
| 452 | 4901044579_1 | 1 | 1 | 1 |
| 453 | 4911040817_1 | 0 | 0 | 0 |
| 454 | 8901043754_1 | 1 | 1 | - |
| 455 | 4701032389_1 | 1 | 0 | - |
| 456 | 4701032307_1 | 1 | 1 | - |
| 457 | 4701034043_1 | 0 | 0 | 0 |
| 458 | 4911041200_1 | 0 | 0 | 0 |
| 459 | 4901043270_1 | 1 | 1 | 1 |
| 460 | 4901044098_1 | 0 | 0 | 0 |
| 461 | 8911041302_1 | 1 | 1 | 1 |
| 462 | 4901045609_1 | 1 | 1 | 1 |
| 463 | 4911042106_2 | 0 | 0 | - |
| 464 | 8911046133_1 | 1 | 1 | - |
| 465 | 4701034581_1 | 1 | 1 | 2 |
| 466 | 4501025625_2 | 1 | 1 | - |
| 467 | 4711030651_2 | 1 | 1 | - |
| 468 | 4901044566_1 | 1 | 1 | 1 |
| 469 | 8711030878_2 | 1 | 1 | 1 |
| 470 | 4501023048_1 | 1 | 1 | 1 |
| 471 | 4701032327_2 | 1 | 1 | 1 |
| 472 | 4911042179_2 | 1 | 1 | 1 |
| 473 | 8911042266_1 | 1 | 2 | - |
| 474 | 4901043840_1 | 1 | 1 | - |
| 475 | 4911041489_1 | 1 | 1 | 1 |
| 476 | 4911041676_1 | 2 | 3 | - |
| 477 | 4701032928_1 | 1 | 1 | - |
| 478 | 4901043713_1 | 0 | 0 | - |
| 479 | 4901044251_1 | 0 | 0 | 0 |
| 480 | 8901043750_1 | 0 | 0 | 0 |
| 481 | 4501023170_2 | 2 | 2 | 1 |
| 482 | 4911042054_1 | 1 | 1 | 1 |
| 483 | 8511020185_1 | 1 | 1 | 1 |
| 484 | 8901044862_1 | 1 | 1 | 1 |
| 485 | 8911046150_1 | 0 | 0 | - |
| 486 | 4701035981_1 | 1 | 1 | 2 |
| 487 | 4901044286_2 | 1 | 0 | - |
| 488 | 4911040654_1 | 1 | 1 | 1 |
| 489 | 4911045543_1 | 1 | 1 | - |
| 490 | 5101053466_2 | 1 | 1 | - |
| 491 | 4701034506_1 | 2 | 2 | 2 |
| 492 | 5101055420_1 | 1 | 1 | - |
| 493 | 5111052113_2 | 1 | 1 | - |

| # | ID_der | PKWHH | | |
|---|---|---|---|---|
| | | First year | Second year | Third year |
| 494 | 5101056280_3 | 2 | 2 | - |
| 495 | 5111050962_2 | 2 | 1 | - |
| 496 | 5101055690_2 | 2 | 2 | - |
| 497 | 4901043583_2 | 1 | 1 | - |
| 498 | 5101055485_2 | 1 | 1 | - |
| 499 | 4701034059_1 | 1 | 1 | 1 |
| 500 | 4901046270_1 | 2 | 2 | - |
| 501 | 5111052479_1 | 1 | 1 | - |
| 502 | 4901045603_1 | 2 | 1 | 1 |
| 503 | 4901043991_1 | 1 | 1 | 1 |
| 504 | 5111050146_1 | 1 | 1 | - |
| 505 | 4711032175_1 | 0 | 0 | 0 |
| 506 | 8711030458_2 | 1 | 1 | - |
| 507 | 5101054512_2 | 2 | 2 | - |
| 508 | 4701032888_1 | 1 | 1 | - |
| 509 | 4901043385_1 | 1 | 1 | 0 |
| 510 | 5101056486_1 | 1 | 1 | - |
| 511 | 8901045915_1 | 0 | 0 | 0 |
| 512 | 5111056619_1 | 2 | 2 | - |
| 513 | 8911042113_1 | 0 | 0 | 0 |
| 514 | 4901044740_1 | 1 | 1 | 1 |
| 515 | 4911042349_1 | 1 | 1 | 1 |
| 516 | 5111051244_1 | 1 | 1 | - |
| 517 | 4911040664_1 | 0 | 0 | 0 |
| 518 | 5101055395_1 | 1 | 1 | - |
| 519 | 5111051809_1 | 1 | 1 | - |
| 520 | 9101055605_1 | 0 | 0 | - |
| 521 | 5101055397_1 | 1 | 1 | - |
| 522 | 4911040697_1 | 1 | 1 | 1 |
| 523 | 8901042750_1 | 2 | 2 | 2 |
| 524 | 4701033254_2 | 2 | 1 | - |
| 525 | 5111052134_1 | 1 | 1 | - |
| 526 | 4911040772_1 | 1 | 1 | - |
| 527 | 4701034591_1 | 2 | 2 | 1 |
| 528 | 5111050295_2 | 2 | 2 | - |
| 529 | 4701033966_1 | 1 | 1 | 1 |
| 530 | 4911040147_1 | 0 | 0 | 0 |
| 531 | 4901044258_1 | 2 | 2 | 2 |
| 532 | 5101055961_1 | 1 | 1 | - |
| 533 | 4701034898_1 | 0 | 0 | 0 |
| 534 | 8911041351_1 | 1 | 1 | 1 |
| 535 | 5111050568_2 | 1 | 2 | - |

| # | ID_der | PKWHH | | |
|---|---|---|---|---|
| | | First year | Second year | Third year |
| 536 | 9101054719_2 | 1 | 1 | - |
| 537 | 9111051561_1 | 1 | 1 | - |
| 538 | 4711031773_1 | 1 | 1 | 1 |
| 539 | 4901044035_1 | 1 | 1 | 1 |
| 540 | 4901044584_1 | 1 | 1 | 1 |
| 541 | 4911045051_2 | 1 | 1 | 1 |
| 542 | 5111051567_1 | 1 | 1 | - |
| 543 | 8711030766_1 | 2 | 2 | 2 |
| 544 | 4711031332_1 | 2 | 2 | 2 |
| 545 | 5101055098_1 | 1 | 1 | - |
| 546 | 4701032565_2 | 2 | 2 | 2 |
| 547 | 4911041511_1 | 2 | 2 | 2 |
| 548 | 4911042255_1 | 2 | 2 | 2 |
| 549 | 5101052641_1 | 2 | 2 | - |
| 550 | 4901042522_1 | 0 | 0 | 0 |
| 551 | 4711031190_1 | 1 | 1 | - |
| 552 | 4911042123_1 | 1 | 1 | - |
| 553 | 5111050931_1 | 1 | 1 | - |
| 554 | 5101053148_1 | 1 | 1 | - |
| 555 | 5111052085_1 | 0 | 1 | - |
| 556 | 5111050256_1 | 1 | 1 | - |
| 557 | 5111050488_1 | 1 | 1 | - |
| 558 | 9111052209_1 | 1 | 1 | - |
| 559 | 4711031609_1 | 2 | 3 | 3 |
| 560 | 4901044592_1 | 0 | 0 | 0 |
| 561 | 4901045871_1 | 1 | 1 | 1 |
| 562 | 4901046289_1 | 0 | 0 | - |
| 563 | 8701034235_1 | 0 | 1 | 1 |
| 564 | 5101053374_1 | 1 | 1 | - |
| 565 | 8701032446_1 | 1 | 1 | - |
| 566 | 5111052455_1 | 1 | 1 | - |
| 567 | 5101052857_1 | 1 | 1 | - |
| 568 | 4711031220_1 | 1 | 1 | 1 |
| 569 | 5101055916_1 | 1 | 1 | - |
| 570 | 5111051243_1 | 0 | 0 | - |
| 571 | 9101054712_1 | 1 | 1 | - |
| 572 | 5101052938_1 | 1 | 1 | - |
| 573 | 5111050121_1 | 0 | 0 | - |
| 574 | 4901044383_2 | 1 | 1 | - |
| 575 | 5101055639_1 | 2 | 2 | - |
| 576 | 5101055582_2 | 2 | 2 | - |
| 577 | 8711032048_2 | 1 | 1 | - |

| # | ID_der | PKWHH | | |
|---|---|---|---|---|
| | | First year | Second year | Third year |
| 578 | 9111051495_2 | 1 | 1 | - |
| 579 | 4911040745_1 | 2 | 2 | 2 |
| 580 | 5101056236_1 | 2 | 2 | - |
| 581 | 8911041011_2 | 2 | 2 | 2 |
| 582 | 4701035105_1 | 1 | 1 | - |
| 583 | 4901042927_1 | 1 | 1 | 1 |
| 584 | 8901043742_1 | 1 | 1 | 1 |
| 585 | 4911041469_1 | 2 | 2 | 1 |
| 586 | 4901044548_2 | 1 | 1 | 1 |
| 587 | 5101053383_1 | 1 | 1 | - |
| 588 | 4701032571_2 | 1 | 1 | 1 |
| 589 | 5101055379_2 | 1 | 1 | - |
| 590 | 5111050715_1 | 2 | 2 | - |
| 591 | 9101053275_1 | 0 | 0 | - |
| 592 | 5101054895_2 | 1 | 1 | - |
| 593 | 5101055116_2 | 1 | 1 | - |
| 594 | 5111051782_1 | 1 | 1 | - |
| 595 | 5101055964_4 | 1 | 2 | - |
| 596 | 5111050876_2 | 1 | 1 | - |
| 597 | 4901044270_1 | 1 | 1 | 1 |
| 598 | 4911042056_1 | 0 | 0 | - |
| 599 | 5101052594_1 | 0 | 0 | - |
| 600 | 9101054897_1 | 1 | 1 | - |
| 601 | 4901043690_1 | 0 | 0 | - |
| 602 | 5111052069_1 | 1 | 1 | - |
| 603 | 8901042721_2 | 1 | 1 | 1 |
| 604 | 4711031398_1 | 1 | 1 | 1 |
| 605 | 5111052058_1 | 1 | 1 | - |
| 606 | 8701032761_1 | 0 | 0 | - |
| 607 | 8901044149_2 | 0 | 0 | - |
| 608 | 4901044295_1 | 0 | 0 | 0 |
| 609 | 4901044795_2 | 1 | 1 | 2 |
| 610 | 9111051931_1 | 0 | 0 | - |
| 611 | 4901042477_1 | 0 | 0 | 0 |
| 612 | 5101055126_2 | 1 | 1 | - |
| 613 | 5111050738_1 | 1 | 1 | - |
| 614 | 5111051822_1 | 1 | 1 | - |
| 615 | 4901044569_1 | 1 | 1 | 1 |
| 616 | 5111051024_1 | 0 | 0 | - |
| 617 | 5111051891_2 | 1 | 1 | - |
| 618 | 8701035896_1 | 2 | 2 | - |
| 619 | 9101053589_1 | 0 | 0 | - |

| # | ID_der | PKWHH | | |
|---|---|---|---|---|
| | | First year | Second year | Third year |
| 620 | 4701033038_1 | 3 | 3 | 1 |
| 621 | 5111050478_2 | 0 | 0 | - |
| 622 | 5111050578_1 | 1 | 1 | - |
| 623 | 9101053019_2 | 0 | 0 | - |
| 624 | 4901044809_2 | 1 | 1 | - |
| 625 | 4911040612_1 | 1 | 1 | 1 |
| 626 | 5111052377_1 | 1 | 1 | - |
| 627 | 8911040163_2 | 1 | 1 | 1 |
| 628 | 4901043658_1 | 1 | 1 | 1 |
| 629 | 5101052848_1 | 2 | 2 | - |
| 630 | 4901044075_1 | 1 | 1 | 1 |
| 631 | 4901046021_1 | 1 | 1 | 1 |
| 632 | 5101054861_1 | 1 | 1 | - |
| 633 | 9101053272_1 | 1 | 1 | - |
| 634 | 5101052963_1 | 1 | 1 | - |
| 635 | 4901042606_1 | 1 | 1 | 1 |
| 636 | 4901044301_1 | 0 | 0 | 0 |
| 637 | 5111050988_1 | 1 | 1 | - |
| 638 | 8911041529_2 | 1 | 1 | 1 |
| 639 | 4911041921_2 | 1 | 1 | 1 |
| 640 | 5101055649_1 | 1 | 1 | - |
| 641 | 4911040185_1 | 2 | 2 | 2 |
| 642 | 4911045015_1 | 1 | 1 | 1 |
| 643 | 5101056010_1 | 0 | 0 | - |
| 644 | 5111051785_1 | 1 | 1 | - |
| 645 | 9101053029_2 | 1 | 1 | - |
| 646 | 5101053102_1 | 0 | 0 | - |
| 647 | 4901043969_1 | 1 | 1 | 1 |
| 648 | 4911041369_1 | 1 | 1 | 1 |
| 649 | 5101054735_1 | 1 | 1 | - |
| 650 | 4901043164_3 | 2 | 2 | - |
| 651 | 4911040464_2 | 0 | 0 | - |
| 652 | 5101055937_1 | 2 | 2 | - |
| 653 | 4901045269_2 | 1 | 1 | 1 |
| 654 | 5101055981_1 | 2 | 2 | - |
| 655 | 4911041969_2 | 2 | 2 | - |
| 656 | 8901045782_1 | 0 | 0 | 0 |
| 657 | 5111051713_2 | 1 | 1 | - |
| 658 | 9111051007_1 | 1 | 1 | - |
| 659 | 4911042126_1 | 1 | 1 | 1 |
| 660 | 8911041251_1 | 2 | 1 | 1 |
| 661 | 4901045262_1 | 1 | 1 | 1 |

| # | ID_der | PKWHH | | |
|---|---|---|---|---|
| | | First year | Second year | Third year |
| 662 | 4901042803_1 | 2 | 2 | 2 |
| 663 | 4901042987_1 | 1 | 1 | 1 |
| 664 | 4901045287_1 | 1 | 1 | - |
| 665 | 5101056145_1 | 2 | 2 | - |
| 666 | 9111050725_1 | 3 | 2 | - |
| 667 | 4911040015_1 | 1 | 1 | 1 |
| 668 | 5111051908_2 | 0 | 0 | - |
| 669 | 8901045317_1 | 1 | 1 | 1 |
| 670 | 4901046070_1 | 2 | 1 | - |
| 671 | 5101054638_1 | 1 | 1 | - |
| 672 | 5101055341_1 | 0 | 0 | - |
| 673 | 8901043421_1 | 0 | 0 | - |
| 674 | 5101053047_1 | 1 | 1 | - |
| 675 | 9111050292_2 | 1 | 1 | - |
| 676 | 4901043839_1 | 2 | 2 | 2 |