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Switching intentions towards car sharing

Analysis of the relationship with traditional transport modes

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Summary

Nowadays car sharing is widespread in several countries; in particular, in Italy, it has been introduced since few years. Advantages of this mean were estimated and reported by many authors. Car sharing can potentially reduce the number of owned cars, the number of performed trips and the relative distance, partially decreasing traffic congestion. Moreover, it contributes to a reduction in energy consumption of travelling, especially through the introduction of electric vehicles in the fleet. However, the quantification of these impacts is often difficult and uncertain. In addition, car sharing can significantly alter the modal share of travellers, since it can substitute or complement existing travel means, with relationships that are still not clear and often site-specific. Previously described benefits can be effective only if car sharing is able to attract private car drivers and, therefore, if it does not substitute other existing sustainable modes (such as public transport, bike and walking). Therefore, estimating and analysing travel demand of this mode is important to evaluate these impacts, thus providing sound basis to policy makers and local authorities, who have to decide whether to address public resources to promote car sharing and to provide travellers with a range of mobility options which can accommodate all their mobility needs.

The aim of the present work of thesis is to identify factors affecting the choice to adopt car sharing and to analyse the relationships of complementarity and/or substitution between car sharing and existing travel modes. Unlike previous works, the effect of car sharing is modelled by separately considering the shift from private car, public transport, bike and walking. Therefore, through the proposed approach, the use of car sharing can be promoted or avoided, by varying mode-specific factors. In the present work of thesis, data from a travel survey carried out in the Turin Metropolitan Area are used. The survey was administered to a representative

sample of the population living in the study area, thereby outcomes of analysis can be generalized to the whole universe of individuals in the area under analysis. Socio-economic characteristic of respondents, their travel diary and related activity patterns spanning over the 24 hours before the interview were collected. Moreover, stated-preference experiments were administered to investigate mode switching attitudes for a randomly selected trip chain, which was effectively performed by the interviewed, thus allowing to obtain reliable results.

In order to reach the aim of the present work, statistical analysis, discrete choice models and data mining techniques are adopted. In particular, first statistical methods are applied to preliminary analyse results of the travel survey, depicting an overview of the current reported scenario. After that, two logistics regressions are implemented, in order to identify users' characteristics that might affect the choice to join a car sharing program and to understand how the characteristics of potential users of car sharing interact with both trip attributes and past and future multimodality behaviours.

Then, in order to predict potential trips carried out on car sharing and to analyse which factors might affect the decision to switch to this mode, three kinds of approaches were developed: a traditional econometric model (a logit model), a data mining technique (Decision Tree model), and a descriptive visual approach. The three proposed methods differ in their basic assumptions; therefore, each approach faces the problem from a different perspective, whereby many results were obtained enriching the analysis about switching intentions towards car sharing. Results of the proposed approaches are complementary and others are common. In particular, the visual approach provided preliminary descriptive analysis on the effect of trip attributes. Moreover, logit models were helpful to understand the effect of different exogenous variables and to derive further information to forecast the consequences of the introduction and diffusion of car sharing on future scenarios. On the other hand, results from Decision Trees were used to identify the non-continuous effects of different variables, by estimating specific thresholds for each factor. However, an overall view of the results of the methods is useful to identify the best ambit of use of each travel means, namely the characteristics of trips which best fit to a specific mode. In this way, it is possible to clarify how car sharing can be effectively introduced to maximize its positive impacts. In addition, alternative mobility scenarios are generated using the estimated models, in order to maximize the number of trips switching from private car towards car sharing and minimize those from public transport and active modes. The results of each scenario are used to analyse the modal split and the effect of car sharing in the use of public space.

Sintesi

Oggigiorno diversi servizi di car sharing sono largamente diffusi in molti Paesi; in particolare, in Italia, sono stati introdotti da pochi anni. I vantaggi derivati dal suo utilizzo sono stati stimati e descritti da vari autori: il car sharing permette, ad esempio, di ridurre le auto privatamente possedute, il numero e la distanze dei viaggi compiuti, favorendo, in tal modo, una minor congestione nelle strade. Oltre a ciò, può contribuire alla riduzione del consumo di energie non rinnovabili utilizzate negli spostamenti, soprattutto grazie alla presenza di veicoli elettrici nella flotta. Tuttavia quantificare tali impatti risulta molto spesso difficoltoso e con risultati incerti. Inoltre, l'introduzione del car sharing può alterare significativamente la ripartizione dei modi di trasporto normalmente utilizzati, dato che questo servizio può potenzialmente sostituire o essere di complemento a tali mezzi, anche se queste relazioni non risultano ancora chiare e dipendono spesso da fattori puntuali, con effetti diversi a seconda del luogo analizzato. I vantaggi precedentemente citati possono verificarsi solamente se il car sharing riesce ad attrarre utenti dal trasporto privato, senza sostituirsi ad altri mezzi più sostenibili, come il trasporto pubblico, la bici o il muoversi a piedi. Per queste ragioni, la stima e l'analisi della domanda di mobilità dei servizi di car sharing risulta necessaria per valutare correttamente gli impatti da essi prodotti. In questo modo le autorità e i decisori pubblici possono avere a disposizione dei solidi strumenti di supporto per indirizzare le risorse della collettività per promuovere o disincentivare l'uso del car sharing, e per fornire agli utenti del sistema un ventaglio di servizi di trasporto che permetta loro di soddisfare ogni esigenza di mobilità.

Lo scopo di questa tesi è di identificare quali sono i fattori che influiscono sulla scelta di utilizzare il car sharing e di analizzare le relazioni di complementarietà o di sostituzione tra tale mezzo e i modi di trasporto esistenti. A differenza degli studi precedenti, gli impatti del car sharing sono stimati considerando separatamente l'auto privata, il trasporto pubblico, la bici e il muoversi a piedi. In questo modo, l'uso dei veicoli condivisi può essere incentivato o meno agendo su variabili diverse per ciascun mezzo considerato. In questa tesi sono stati utilizzati dati derivanti da un'indagine di mobilità realizzata nell'Area Metropolitana di Torino. Tale questionario è stato somministrato ad un campione stratificato statisticamente rappresentativo della popolazione residente nell'area di studio; in tal modo, i risultati delle successive analisi possono essere espansi all'universo. Attraverso questa indagine sono state rilevate le caratteristiche socio economiche degli intervistati, il loro diario di viaggio e le relative attività compiute nelle 24 ore precedenti l'intervista. Inoltre, ciascun individuo è stato sottoposto ad esperimenti di scelte dichiarate, con lo scopo di valutare le attitudini al cambio modale per una catena di spostamenti selezionata casualmente e che è stata realmente compiuta dall'intervistato, permettendo così di ottenere risultati affidabili.

Per raggiungere lo scopo prefissato, in questa tesi sono state impiegati metodi di analisi statistica, modelli di scelta discreti e tecniche di data mining. In particolare, in primo luogo i risultati dell'indagine sono stati preliminarmente analizzati attraverso metodi statistici, in modo da ottenere una visione generale dello scenario di mobilità rilevato. In seguito, sono state implementate due regressioni logistiche con lo scopo di identificare le caratteristiche che influiscono sulla scelta di iscriversi al car sharing e di capire come tali variabili interagiscono sia con gli attributi dello spostamento che con i comportamenti multimodali passati e futuri dell'intervistato.

Successivamente, sono stati sviluppati tre diversi approcci per ottenere una previsione degli spostamenti che potenzialmente possono essere effettuati su veicoli condivisi e per analizzare quali fattori possono indurre al cambio modale. In particolare sono stati considerati dei modelli basati sulla teoria econometrica (modelli logit), tecniche di data mining (alberi decisionali) e un approccio visivo-descrittivo. Tali metodi differiscono per le assunzioni alla base, perciò ciascuno di essi permette di affrontare il problema da una diversa prospettiva. In questo modo, i relativi risultati contribuiscono ad arricchire l'analisi sulla propensione all'uso del car sharing, essendo complementari o simili tra i diversi approcci. Nello specifico, il metodo visivo-descrittivo ha permesso di effettuare un'analisi preliminare degli effetti degli attributi degli spostamenti. I modelli logit sono stati usati per capire l'effetto di diverse variabili esogene e per quantificare le previsioni sugli impatti dell'introduzione del car sharing in scenari futuri. Inoltre, gli alberi decisionali sono stati impiegati per identificare gli effetti discontinui di alcune variabili, stimando i punti di discontinuità per ciascun fattore. Tuttavia, considerato congiuntamente i risultati di tutti i metodi adottati è stato possibile delineare gli ambiti d'uso di ciascun modo di spostamento, ossia quali sono le caratteristiche che un generico spostamento dovrebbe avere per essere compiuto con uno specifico mezzo di trasporto. In questo modo è possibile chiarire come l'uso dei veicoli condivisi può essere indirizzato per massimizzarne gli impatti positivi. Inoltre, sono stati generati degli scenari alternativi applicando i modelli calibrati in precedenza, con lo scopo di massimizzare il numero di spostamenti in auto sostituiti dal car sharing e minimizzare quelli in trasporto pubblico, bici e piedi che tale nuovo modo di trasporto ha sostituito. I risultati di ciascuno scenario sono stati utilizzati per valutare la ripartizione modale e gli effetti del car sharing sull'uso del suolo pubblico.

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Chapter 1

Introduction

Nowadays car sharing is widespread in several countries; in particular, in Italy, it has been introduced since few years. Social, environmental and land use impacts of car sharing have been extensively analysed by several authors. Most of them are positive, such as a reduction of car ownership, due to users who decide to dispose an owned vehicle or not to buy an extra car after joining the service. This contributes to decrease the parking space occupied by private vehicles; in this way, cities with limited public areas can gain further space for different land uses. The decreasing private car usage induces travellers to adopt alternative and more sustainable transport modes, such as public transport, bike and walking. Furthermore, the introduction of car sharing is found to reduce vehicle miles travelled, since users lowered the number of their private cars; in addition, they became more conscious of driving cost and, consequently, they used vehicles more appropriately, shortening travel distances. Moreover, car sharing contributes to reduce carbon fossil emissions, as a consequence of these aspects and since fleets are often equipped with efficient low-emission or electric engines. However, the quantification of these impacts is often difficult and uncertain, due to the complexity of this evaluation. Therefore, estimating and analysing travel demand of this mode is important to evaluate these impacts, thus providing sound basis to policy makers and local authorities, who have to decide whether to address public resources to promote car sharing.

Furthermore, car sharing can significantly alter the modal share of travellers, since it can substitute or complement existing travel means, with relationships that are still not clear and often site-specific. In particular, car sharing can complement public transport solving the "first and last miles" problem, increasing its spatial and temporal accessibility, since car sharing can be used in areas with low public transport penetration or in time periods when it is less frequent. However, car sharing can also substitute transit for systematic trips. This controversial relationship can change according to car sharing operational model, due to different types of trips which can be addressed by each service model. The same ambiguity is reported for bike, walking and taxi. Moreover, competitiveness can arise even among car sharing operators with different business models within the same city. The analysis of complementarity and substitution patterns can help transportation planners and policy makers in providing travellers with a range of mobility options which can accommodates all their mobility needs. In addition, previously described benefits can be effective only if car sharing is able to attract private car drivers and, therefore, if it does not substitute other existing sustainable modes (such as public transport, bike and walking). According to this last consideration, few authors developed specific analyses for each transport mode that car sharing can substitute. Furthermore, only a few authors carried out their analysis on a representative sample of the population, for example by targeting their studies on a specific segment of transport system users. For this reason, results are not always generalizable and reliable.

The aim of the present work of thesis is to identify factors affecting the choice to switch to car sharing and the relationships of complementarity and/or substitution between car sharing and existing travel modes. Unlike previous works, the effect of car sharing on other travel means is modelled by separately considering the shift from private car, public transport, bike and walking. Therefore, through the proposed approach, the use of car sharing can be promoted or avoided, by varying mode-specific factors. Furthermore, different methods to model car sharing switching intentions are adopted and results are compared. In particular, Random Utility Models, Decision Trees and a descriptive visual approach are applied to understand variables affecting the choice of using this service. Each of these three approaches provides different considerations, from different perspectives, contributing to enrich the global view on the relationship between car sharing and traditional transport means. Since each method has a different basis, some results are complementary and others are common. However, an overall view of the results of the methods can identify the best ambit of use of each travel means, namely the characteristics of trips which best fit to a specific mode. In this way, it is possible to clarify how car sharing can be effectively introduced to maximize its positive impacts.

In addition, alternative mobility scenarios are generated using the estimated models, in order to maximize the number of trips switching from private car towards car sharing and minimize those from public transport and active modes. The results of each scenario are used to analyse the modal split and the effect of car sharing in the use of public space. Indeed, one of the advantages of this transport mode is to reduce the on-street parking space that private cars usually occupy. However, in many previous works, the reduction of the demand for parking spaces is often associated with a reduction of car ownership due to car-sharing, so that several papers quantified how many private cars could be replaced by a shared vehicle. Yet positive benefits on public spaces might be observed, albeit to a lesser extent, even if the private car is not given up, since the parking pressure near the main mobility attractors might be reduced. Therefore, without considering changes in car ownership levels, which are related to long term effects, in the present work, trip-level impacts on parking spaces, which might occur in short-medium periods, are estimated, by analysing variations in the spatial configuration of the demand for car parking spaces after the introduction of car sharing.

The present thesis is organized as follows. The first chapter contains the analysis of the state of the art, reporting the definition of car sharing and its operative models, the factors affecting car sharing membership, the main advantages, and the data sources and methods adopted to study several aspects related to the introduction and development of this transport mode. After that, results of preliminary statistical analysis of data from the travel survey adopted in the present work are presented. The next chapter contains the outcomes of the calibration of models to analyse factors affecting the car sharing membership, the propensity to use this service and the intentions to switch from private car, public transport bike and walking towards car sharing. In particular, the last group of models includes Random Utility based Models, Decision Trees and a descriptive visual approach. Then, in the last chapter, different mobility scenarios are generated by applying results of the previously estimated models, in order to evaluate the modal split and to quantify the impacts of the introduction of car sharing on parking space.

Chapter 2

State of art

In this chapter, a literature review regarding car sharing and its effects is presented, in order to describe the current state of the art, which was analysed as a starting point for this work of thesis. Due to the great amount of different aspects related to car sharing, tackled in previous works, the presentation of the considered literature was structured according to the following logical framework, which was visualized in Figure 1. In particular, first, in a introductive section (2.1), impacts of the car dependency which was observed in many current transportation systems was presented (section 2.1.1); in order to overcome the reported drawbacks, several alternative sustainable transport solutions were proposed by many authors and local authorities (section 2.1.2). Car sharing is one of the cited sustainable transport modes (section 2.1.3), which has shown a great diffusion in the last years in many cities, worldwide (section 2.1.4). For this reason and in order to take benefits from car sharing advantages, many local authorities had to consider this new travel modes in transportation planning activities (section 2.1.5). In order to create sound basis for the current work of thesis, an analysis of car sharing definitions (section 2.2.1), operational models (section 2.2.2) and characteristics of business models (section 2.2.3) was carried out. After that, in order to deeply understand both the causes and effects in mobility habitudes of car sharing diffusion, variables affecting its adoption (section 2.3) and its relationship with other transport means (section 2.4) were analysed. In particular, both existing sustainable travel modes, such as public transport (section 2.4.1), bike, walking (section 2.4.2), taxi (section 2.4.3), and other car sharing services (section 2.4.4) were considered. Due to the reported changes in the modal split and travel habits of users, car sharing can produce many positive impacts (section 2.5), for instance the reduction of car ownership (section 2.5.1), a decreasing parking space (section 2.5.2), an increasing use of sustainable modes (section 2.5.3), a reduction of Vehicle Miles Travelled (section 2.5.4) and it contributes to lower polluting emissions (section 2.5.5). Since the quantification of these effects is often complex (section 2.5.6), different data sources (section 2.6.1) and many methods (section 2.6.2) were proposed and adopted by previous authors. In the final section (2.7), concluding remarks were reported as a starting point for the present work; moreover, existing research gaps were pointed out, in order to address potential improvements which this thesis might add to the debate about car sharing and its effects.

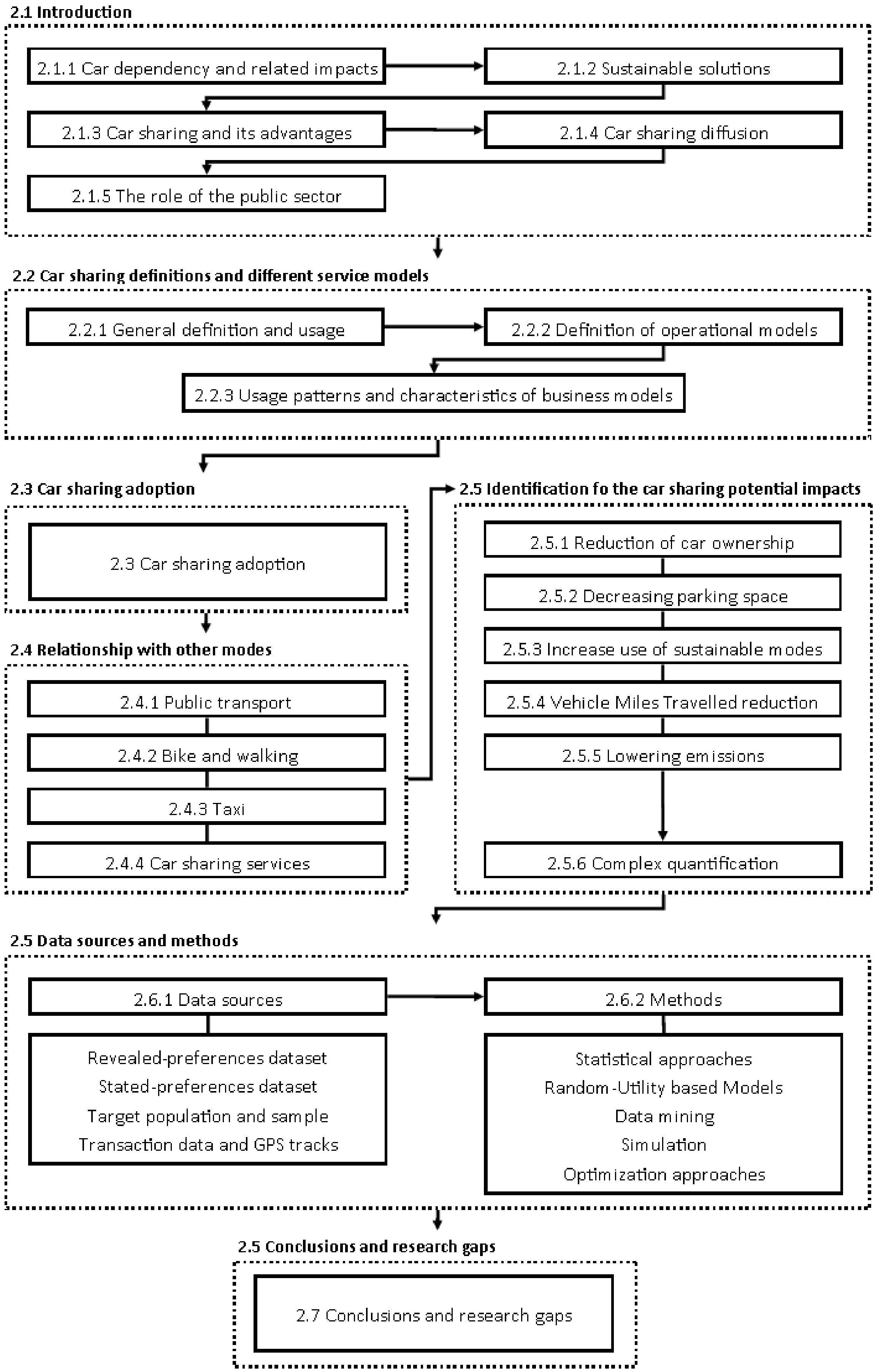

Figure 1. Diagram of the literature review sections

2.1. Introduction

2.1.1. Car dependency and related impacts

For decades, private car has been the preferred mode of transport in urban contests. People enjoy travelling by car (Huwer, 2004), since, because of its flexibility (Habib et al., 2012; Kaspi et al., 2014; Morency et al., 2012) and accessibility (Jorge and Correia, 2013), it is perceived as a transport means which can be adapted to every individual's daily needs (Nobis, 2007). Furthermore, in a society characterized by individualized lifestyle (Nobis, 2007), private car is considered as a status symbol (Schmöller et al., 2015; Steg, 2005), i.e. car owners buy and use vehicles to show off identity, personality and social status (Webb, 2019). Moreover, in the past decades, the use of private car was encouraged (Schmöller et al., 2015). In addition, partly because of a growing urbanization (Mounce and Nelson, 2019), a lot of infrastructures were built in order to provide an efficient and quick flow of vehicles, deeply influencing the structure of urban areas (Burghard and Dütschke, 2019; de Lorimier and El-Geneidy, 2012; Schmöller et al., 2015). This results in a high car dependency (de Lorimier and El-Geneidy, 2012; Nobis, 2007), leading to an increasing car ownership rate experienced in many countries (Habib et al., 2012; Morency et al., 2012).

However a massive car usage has some negative externalities (Firnkorn and Shaheen, 2016; Jorge and Correia, 2013), producing serious impacts on citizens' quality of life (Catalano et al., 2008). Traffic congestion is an everyday problem in our cities (Carroll et al., 2017; Choudhury et al., 2017; El Zarwi et al., 2017; Glotz-Richter, 2016; Habib et al., 2012; Lee et al., 2016; Lempert et al., 2019; Morency et al., 2012; Shaheen and Cohen, 2007), particularly during peak hours when most of the people adopts private car to commute to work and to go to school (Carroll et al., 2017), often with low occupancy rates of vehicles (Choudhury et al., 2017). This causes high travel times for daily trips (Catalano et al., 2008; Jorge and Correia, 2013), which is subtracted from other activities (Jorge et al., 2015a), with implications even for the economy (Carroll et al., 2017). Moreover, the vast majority of existing cars on the roads are equipped with internal combustion engines powered by fossil fuels, thus negatively contributing to climate change (Burghard and Dütschke, 2019; El Zarwi et al., 2017). Indeed the great diffusion of conventional private vehicles produces polluting and greenhouse gas emissions (Carroll et al., 2017; Catalano et al., 2008; El Zarwi et al., 2017; Firnkorn and Shaheen, 2016; Jorge and Correia, 2013; Kim et al., 2017a; Lee et al., 2016; Lempert et al., 2019) and an over-use of non-renewable resources (Burghard and Dütschke, 2019; Kim et al., 2017a; Lee et al., 2016; Schlüter and Weyer, 2019), causing dangerous environmental problems (Kim et al., 2017b). In addition, since private cars are parked for about 95% of their lifetime (Kim et al., 2017a; Morency et al., 2015; Mounce and Nelson, 2019; Namazu et al., 2018), they contribute to reduce the limited availability of public space in urban contests (Firnkorn and Shaheen, 2016; Glotz-Richter, 2016; Kaspi et al., 2014; Kim et al., 2017a; Shaheen and Cohen, 2007). Furthermore, high car traffic flows often produce a harmful effect of noise pollution (Carroll et al., 2017; Catalano et al., 2008). Finally, in the last years, car users had to experience the increasing of costs associated with the ownership and usage of cars (Jorge et al., 2015a), such as purchase, insurance and maintenance cost (Efthymiou et al., 2013; Jorge and Correia, 2013). In particular, the cost of fuels grew due to the general trend of energy prices (Efthymiou et al., 2013; Shaheen and Cohen, 2007), and parking costs raised due to the continuous reduction of public space (Clewlow, 2016; Shaheen and Cohen, 2007).

2.1.2. Sustainable solutions

In order to overcome these drawback, policy makers implemented strategies to promote sustainable mobility (Clewlow, 2016; El Zarwi et al., 2017; Martin and Shaheen, 2011a, 2011b). In particular, the increasing awareness of environment (Carroll et al., 2017; Clewlow, 2016; Martin and Shaheen, 2011b) and the more restrictive rules about emissions (Habib et al., 2012; Morency et al., 2012; Shaheen et al., 2011), prompted authorities to adopt policies reducing the use of private vehicles, such as car-free zones, congestion charging and low emission zones (Mounce and Nelson, 2019), and to consider more sustainable travel means (Burghard and Dütschke, 2019; Clewlow, 2016; Mounce and Nelson, 2019; Shaheen and Cohen, 2013). Among them, active modes, like walking and cycling can significantly reduce the carbon footprint (de Lorimier and El-Geneidy, 2012) and provide great flexibility (Huwer, 2004), however, they are not suitable for families and to carry goods (de Lorimier and El-Geneidy, 2012). Moreover, they are limited by distance and they require physical efforts (Huwer, 2004). On the other hand, traditional public transport is a sustainable alternative which can solve some of the previously described problems (de Lorimier and El-Geneidy, 2012; Jorge et al., 2015a; Jorge and Correia, 2013; Kim et al., 2017a). However, if compared to car, it has some drawbacks (Jorge et al., 2015a; Jorge and Correia, 2013), making a complete substitution of private vehicle very difficult. In detail, public transit does not provide enough flexibility for every trip purpose (Huwer, 2004), due to fixed scheduled frequencies (Jorge et al., 2015a) and limited operating periods (Kaspi et al., 2014). Moreover, it requires high investment costs (Jorge et al., 2015a) through public resources, and it does not guarantee the privacy of passengers (Kaspi et al., 2014). Furthermore, it often has limited service areas (Jorge et al., 2015a; Jorge and Correia, 2013; Kaspi et al., 2014) and accessibility (Kim et al., 2017a), thus generating troubles for people living far from a public transport station or stop (Kaspi et al., 2014). Therefore, due to these disadvantages, users still prefer ravelling by private car (Kaspi et al., 2014).

2.1.3. Car sharing and its advantages

Considering these drawbacks, car sharing can fill the gap between private car and public transport (Efthymiou et al., 2013; Kaspi et al., 2014; Morency et al., 2007), since it allows users to enjoy the privacy and flexibility of private car (Barth and Shaheen, 2002; Clewlow, 2016; Zhou and Kockelman, 2011) without directly bearing all the associated costs (Cooper et al., 2000; Costain et al., 2012b; de Lorimier and El-Geneidy, 2012; de Luca and Di Pace, 2015; Efthymiou et al., 2013; Efthymiou and Antoniou, 2016; Hua et al., 2019; Huwer, 2004; Jones and Leibowicz, 2019; Kim et al., 2017a; Martin and Shaheen, 2011a; Shaheen et al., 2006; Shaheen and Chan, 2016; Shaheen and Cohen, 2013; Yoon et al., 2017) and constraints (Coll et al., 2014). From this point of view, car sharing is considered a mix between private vehicle and public transit (Habib et al., 2012; Morency et al., 2012), since it provides the same freedom and advantages of the former (Martin and Shaheen, 2011a) with affordable prices (Barth and Shaheen, 2002; Priya Uteng et al., 2019), like the latter. Furthermore, car sharing is a sustainable transport mode (Lagadic et al., 2019; Priya Uteng et al., 2019), since it potentially reduces car ownership (Catalano et al., 2008; de Luca and Di Pace, 2015; Jin et al., 2018; Lempert et al., 2019) and the number of private vehicles required to satisfy the total travel demand (Barth and Shaheen, 2002; Morency et al., 2015), thus increasing the availability of public space (Barth and Shaheen, 2002; Catalano et al., 2008; Huwer, 2004; Lagadic et al., 2019) and reducing traffic congestion (Lee et al., 2016).

Moreover, car sharing vehicles are often equipped with low-polluting engines (Barth and Shaheen, 2002; Catalano et al., 2008), such as electric power (Burghard and Dütschke, 2019). In addition, it encourages the adoption and the future purchase of private electric vehicles (Cartenì et al., 2016; Schlüter and Weyer, 2019). In this way, car sharing can decrease greenhouse gas emission (Jorge et al., 2015b; Lempert et al., 2019; Martin and Shaheen, 2011b; Rabbitt and Ghosh, 2013). Furthermore, car sharing can change mobility habits (Barth and Shaheen, 2002; Le Vine et al., 2014a; Zhou, 2012), since users are more aware of the cost of driving (Catalano et al., 2008; Efthymiou and Antoniou, 2016; Zheng et al., 2009). For instance, car sharing increases the use of public transport (Lempert et al., 2019), providing a complementary travel mode (Clewlow, 2016). Therefore car sharing offers the opportunity to contribute to sustainable urban development (Jorge et al., 2015a), without forcing travellers to forgo the advantages of driving a car (Huwer, 2004). According to this point of view, car sharing does not delete car usage, but it makes users aware of how properly using a vehicle (Coll et al., 2014; de Lorimier and El-Geneidy, 2012; Huwer, 2004; Morency et al., 2015). Even if car sharing cannot provide users with exactly the same benefits of private vehicles (Priya Uteng et al., 2019), compared to a past context where private car, public transport, taxi, bike and walking where the main travel means (Becker et al., 2017c), nowadays car sharing is a new mobility option (Barth and Shaheen, 2002), which allows users to choose the transport mode which can best accommodate their mobility needs (Becker et al., 2017c; de Luca and Di Pace, 2015; Huwer, 2004; Jorge et al., 2015a).

2.1.4. Car sharing diffusion

The first car sharing implementation took place in Switzerland in 1948 (Becker et al., 2017a; Shaheen et al., 1999; Shaheen and Cohen, 2007), however only in recent years car sharing has become widespread (Clewlow, 2016; Lempert et al., 2019; Morency et al., 2015), becoming an usual mobility option throughout the world (Costain et al., 2012b; Shaheen and Cohen, 2007), even in Italy (Rotaris et al., 2019). Besides to the previously explained advantages of car sharing, its rapid growth was due to the diffusion of Information and Communication Technologies (Becker et al., 2017a; Clewlow and Mishra, 2017; Lempert et al., 2019; Morency et al., 2015; Standing et al., 2019). In particular, Global Positioning System and communication network allow users and operators to trace the position of a shared vehicle (Kaspi et al., 2014; Shaheen and Chan, 2016); this information is made available anywhere and whenever needed (Kaspi et al., 2014). Moreover, car sharing is an element of the sharing economy (Glotz-Richter, 2016; Jin et al., 2018), which is penetrating even in the transportation sector (Jin et al., 2018). Indeed, according to this perspective, car sharing decreases the demand of new products and increases the use of existing ones, since it offers the possibility to go on using (shared) car, whenever needed (Huwer, 2004), without purchasing a new private vehicle (Jin et al., 2018). Finally, many young adults living in developed countries decide to postpone to acquire a driving licence (Mounce and Nelson, 2019); this suggests that owning a car is gradually becoming less important (Schmöller et al., 2015). These reasons foster the shift from car ownership to “car as demand” (Firnkorn and Müller, 2012; Kent and Dowling, 2016a; Mounce and Nelson, 2019).

2.1.5. The role of the public sector

Due to the recent diffusion of car sharing, policy makers have to face its importance both as a new mobility option for users and as a new market opportunity for operators. From the first point of view, local authorities should manage the relationship of car sharing with other existing transport means (Terrien et al., 2016; Welch et al., 2018), such as public transport (de Luca and Di Pace, 2015; Firnkorn and Müller, 2011). Properly integrating car sharing in planning policy (Glotz-Richter, 2016; Lagadic et al., 2019) towards a Mobility as a Service (MaaS) perspective (Lagadic et al., 2019), they can offer users the best combination of mobility opportunities that can accommodate all their mobility needs (Firnkorn and Müller, 2011), in terms of flexibility and accessibility (Huwer, 2004). Moreover, considering previously explained advantages, policy makers should promote car sharing as a means to reach sustainability goals (Habib et al., 2012; Lagadic et al., 2019; Morency et al., 2012). From the second point of view, local authorities have to discuss with car sharing operators in order to address public resources towards the implementation of a car sharing program (Ceccato and Diana, 2018; Shaheen et al., 2006). In particular, policy makers can decide to provide financial support (Lagadic et al., 2019) or to fix fares in order to reduce competition with public transport (Gordon-Harris, 2016; Mounce and Nelson, 2019). Moreover they can allow public parking spaces (Becker et al., 2018; Dowling and Kent, 2015; Gordon-Harris, 2016; Kent and Dowling, 2016b; Lagadic et al., 2019; Le Vine et al., 2014b, 2014a; Mounce and Nelson, 2019; Shaheen et al., 2011; Stasko et al., 2013; Terrien et al., 2016), the use of public transit reserved lanes or free access to limited traffic areas (Ceccato and Diana, 2018). Furthermore, they can indicate the location of charging infrastructures for shared electric vehicles (Gordon-Harris, 2016; Mounce and Nelson, 2019). Finally, local authorities have the possibility to promote car sharing to citizens (Stasko et al., 2013), in order to foster its diffusion (Lagadic et al., 2019).

In order to provide sound basis for local authorities, as a support for policies, which promote and manage car sharing (Ceccato and Diana, 2018), this new travel mode has to be introduced in travel demand modelling. In this way, it is possible to forecast and to quantify the effects of car sharing on travel behaviour (Becker et al., 2018; Dias et al., 2017; Martin and Shaheen, 2011a) and, consequently, on the transport system, environment (Terrien et al., 2016) and society (Namazu et al., 2018; Rotaris et al., 2019).

2.2. Car sharing definitions and different service models

2.2.1. General definition and usage

In literature there are many definitions of car sharing, reporting a very similar concept. Car sharing is a service in which members can use a vehicle of the fleet by paying a fee, whenever they need (Efthymiou and Antoniou, 2016; Jones and Leibowicz, 2019; Shaheen et al., 2006; Shaheen and Chan, 2016). The shared car can be used 24 hours a day (Huwer, 2004; Shaheen et al., 2015) and with a short-term access (Kent and Dowling, 2016b; Morsche et al., 2019; Shaheen and Chan, 2016; Shaheen et al., 2015; Stillwater et al., 2009), even less than one hour (Huwer, 2004; Mounce and Nelson, 2019). The fee is calculated on a trip basis (Ferrero et al., 2018), i.e. it depends on the vehicle usage (Efthymiou et al., 2013; Jian et al., 2017; Shaheen et al., 2011), in particular on distance and/or duration of the trip (Efthymiou and Antoniou, 2016; Huwer, 2004; Juschten et al., 2017; Stillwater et al., 2009). Depending on the business model, the fee includes maintenance, insurance, fuel, parking and congestion charging (Alonso-Almeida, 2019; Efthymiou et al., 2013; Shaheen and Chan, 2016; Shaheen and Cohen, 2013; Stillwater et al., 2009), furthermore, users pay also a membership fee (Ciari et al., 2015; Efthymiou and Antoniou, 2016; Kim et al., 2017a). On the other hand, depending on the business model, a car sharing operator provides the service, vehicles and their maintenance (Huwer, 2004; Kim et al., 2017a; Mounce and Nelson, 2019; Shaheen et al., 2006). After becoming a member, users can locate the position of each shared vehicle and book it in real time, online or by a smartphone app (Efthymiou and Antoniou, 2016; Juschten et al., 2017; Kent and Dowling, 2016b; Kim et al., 2017a, 2017b; Morsche et al., 2019). After that, they can open the vehicle through a personal identification system and drive (Efthymiou and Antoniou, 2016). At the end of their trip, they return the vehicle (Jones and Leibowicz, 2019) and the system show them the exact cost of the trip that they must pay (Efthymiou and Antoniou, 2016; Kent and Dowling, 2016b). Thus, the vehicle is available to the next users; in this way, a single vehicle can be used by many persons at different time periods (Fleury et al., 2017).

Car sharing is different from traditional car rental, since it allows short-terms access (Lagadic et al., 2019), indeed fares are based on minutes or hours (Ciari et al., 2015), not on day or weeks (Alonso-Almeida, 2019). Moreover, in car rental, vehicles are borrowed under a contract and picked up from centralized and staffed locations for each rent (Stillwater et al., 2009). On the contrary, in most of car sharing services, a single contract is stipulated in the subscription phase (Rodenbach et al., 2018), and shared cars are booked and picked up directly by the user (Juschten et al., 2017; Shaheen et al., 2006; Shaheen and Chan, 2016; Stillwater et al., 2009; Terrien et al., 2016).

2.2.2. Definitions of operational models

Car sharing systems have many business models, which can be grouped in the following types (Lagadic et al., 2019): Buyer-to-Customer (B2C), Peer-To-Peer (P2P) and Corporate (B2B). In B2C services an operator provides the service to the public (Lagadic et al., 2019; Rodenbach et al., 2018). This service can be Round-trip or One-way (Dill et al., 2019; Lagadic et al., 2019; Le Vine et al., 2014a, 2014b; Lempert et al., 2019; Martin and Shaheen, 2016; Martínez et al., 2017; Namazu and Dowlatabadi, 2018). Round-trip [or Two-way (Barth and Shaheen, 2002; Efthymiou and Antoniou, 2016)] system can be further divided into Station-based and Home zone-based. In the first case, users pick up and return the shared vehicle in the same reserved parking spot (Alonso-Almeida, 2019; Ferrero et al., 2018; Firnkorn and Shaheen, 2016; Glotz-Richter, 2016; Guirao et al., 2018; Illgen and Höck, 2018; Jorge and Correia, 2013; Juschten et al., 2017; Kent and Dowling, 2016b; Lagadic et al., 2019; Le Vine et al., 2014a; Rodenbach et al., 2018; Rotaris and Danielis, 2018; Shaheen and Chan, 2016); whereas, in the second case, users pick up and drop off the vehicle in the same zone of the city (Firnkorn and Shaheen, 2016; Rodenbach et al., 2018). Moreover, One-way car sharing can be Station-based or Free-floating (Alonso-Almeida, 2019; Lagadic et al., 2019; Martin and Shaheen, 2016; Rotaris and Danielis, 2018; Shaheen and Chan, 2016; Shaheen et al., 2015). In a One-way Station-based service model users pick up the vehicle in a reserved parking spot and can return it in a different one (Alonso-Almeida, 2019; Barth and Shaheen, 2002; Ciari et al., 2014; Efthymiou and Antoniou, 2016; Ferrero et al., 2018; Firnkorn and Shaheen, 2016; Guirao et al., 2018; Illgen and Höck, 2018; Jorge and Correia, 2013; Kaspi et al., 2014; Lagadic et al., 2019; Le Vine and Polak, 2019; Martin and Shaheen, 2016; Martínez et al., 2017; Namazu and Dowlatabadi, 2018; Shaheen et al., 2015). On the other hand, in a Free-floating system, users can pick up and drop off a shared vehicle everywhere within a service area (Alonso-Almeida, 2019; Becker et al., 2018, 2017b, 2017a;

Ciari et al., 2015, 2014; Ferrero et al., 2018; Firnkorn and Müller, 2011; Firnkorn and Shaheen, 2016; Glotz-Richter, 2016; Juschten et al., 2017; Kaspi et al., 2014; Kent and Dowling, 2016b; Lagadic et al., 2019; Le Vine and Polak, 2019; Lempert et al., 2019; Martin and Shaheen, 2016; Martínez et al., 2017; Namazu and Dowlatabadi, 2018; Shaheen et al., 2015). In addition, some authors presented a car sharing system which can operate with a Round-trip in normal conditions, and with an One-way model for specific points in a city, which generates high demand (e.g. airports) (Jorge et al., 2015a).

In Peer-To-Peer (P2P) car sharing, a private vehicle owner can share her car directly with other private users, through a platform provided by an external operator (Alonso-Almeida, 2019; Dill et al., 2019; Glotz-Richter, 2016; Lagadic et al., 2019; Martin and Shaheen, 2016; Rotaris and Danielis, 2018; Shaheen et al., 2018, 2015). In this case, the vehicle can be accessed by face-to-face interactions or through a specific device in the car (Lagadic et al., 2019).

In Corporate (B2B) car sharing, members of the service are employed in a firm and the fleet is owned and/or managed directly by the firm or by a third-party operator (Clark et al., 2015; Fleury et al., 2017; Lagadic et al., 2019; Shaheen and Wright, 2001). Therefore B2B model is characterized by an employer-base use, i.e. for business trips (Fleury et al., 2017), unlike B2C, which has a personal use (Clark et al., 2015).

2.2.3. Usage patterns and characteristics of business models

Each service model has different characteristics, usage and advantages (Alonso-Almeida, 2019). Concerning B2C services, different car sharing business models can be ranked by the flexibility that they provide to users (Firnkorn and Shaheen, 2016). In particular, the lowest flexibility is offered by Round-trip systems, since returning the shared vehicle to the original location is a constraint for activities that could be potentially carried out through car sharing (Ciari et al., 2014; Firnkorn and Shaheen, 2016; Jorge et al., 2015a). In particular, activities correlated with this system are often short (Barth and Shaheen, 2002; Costain et al., 2012b), since the duration of activities is included in the rental period, therefore users have to pay for it (Ciari et al., 2014). For this reason, since commuting trips require a long time at parks (Jorge et al., 2015a), they are not suitable for this model (Ciari et al., 2014). Therefore Round-trip is often used for leisure trips (Barth and Shaheen, 2002; Firnkorn and Müller, 2011). Furthermore, since users are required to book in advance the vehicle (Ciari et al., 2014; Le Vine et al., 2014b; Le Vine and Polak, 2019), the system ensures the availability of the car thus offering great reliability to members (Glotz-Richter, 2016).

On the other hand, One-way Station-based system provides more flexibility than the previous model (Barth and Shaheen, 2002; Firnkorn and Shaheen, 2016). Finally, the highest levels of flexibility are reached by One-way Free-floating systems (Ciari et al., 2014; Firnkorn and Shaheen, 2016; Juschten et al., 2017; Le Vine et al., 2014b; Seign et al., 2015; Shaheen and Chan, 2016), which has recently been introduced (Becker et al., 2017b; Guirao et al., 2018) and it overcomes some limitations of the traditional Round-trip system (Becker et al., 2018; Namazu and Dowlatabadi, 2018): the need to advance reservation and to drop off the shared car in the starting station (Ciari et al., 2014; Guirao et al., 2018). Indeed, this service allows users to locate the closest available vehicles in real time (Becker et al., 2018, 2017b; Guirao et al., 2018; Namazu and Dowlatabadi, 2018). However they can book the shared car for a short time prior to their rental (15 minutes) (Becker et al., 2018, 2017b), therefore this system does not guarantee to find an available vehicle near a desired activity location (Ciari et al., 2014; Le Vine et al., 2014b). Introducing car sharing in an agent-based simulation, Ciari et al. (Ciari et al., 2014) reported that Free-floating can be adopted even for commuting trips, unlike Round-trip system, suggesting that these two services might be complementary. On the contrary, analysing transaction data of a Free-floating car sharing provider in Switzerland, Becker et al. (Becker et al., 2017b) found that this system is mostly used for discretionary trips. In a later work, the same authors confirmed this result and identified patterns that could be performed both with Free-floating and Station-based car sharing, suggesting that they can complement or compete each other (Becker et al., 2018). In conclusion, Free-floating car sharing can accommodate more trip purposes than Round-trip (Jorge et al., 2015a; Jorge and Correia, 2013). Nevertheless, this system lead to an imbalanced distribution of the fleet, due to its great flexibility (Jorge et al., 2015b; Jorge and Correia, 2013; Terrien et al., 2016).

On the contrary, P2P car sharing has high levels of flexibility at lower costs, respect to other services (Alonso-Almeida, 2019; Shaheen et al., 2018). Indeed, in this case, the operator does not bear the cost of purchase and maintenance of the fleet, furthermore car owners do not spend to make their car attractive and they accept to get a low revenue for the sharing, since they do not expect to make a profit (Dill et al., 2019). Moreover, P2P car sharing can overcome the geographical limitation of traditional car sharing. In particular, in order to increase earnings, car sharing operators usually concentrate their vehicles where there is a high potential demand, thus decreasing the accessibility of other zones (Dill et al., 2019). On the contrary, P2P shared cars tend to be widespread throughout the city. Furthermore, in a P2P system, the range of vehicle types that users can access is usually wider than those of B2C and B2B services (Shaheen et al., 2018).

2.3. Car sharing adoption

In order to forecast the impacts of car sharing on travel demand, network performances and land use, it is important to understand factors affecting the adoption and the use of this service (Dias et al., 2017). Table 1 shows the main variables that were found to significantly affect the user's choice to join a car sharing program and the usage frequency of car sharing. Factors were aggregated in the following groups: socio-economic variables both at individual and household level, characteristics of a specific trip under analysis, travel habits and personal awareness of potential adopter. Effects of each variable were classified as: positive, negative or specific, i.e. the impact of a variable was estimated only for a particular class of that variable. Furthermore, the "unspecified" category includes works where a factor was considered, but the related effect was not explained, sometimes because it was introduced in wide models, such as Agent-Based models (Ciari et al., 2015). Observing this table, one can note that opposite effects are often reported for the same variables, by different authors (Ceccato and Diana, 2018). This might be due to the adopted analysis technique (Efthymiou and Antoniou, 2016) or since factors are site-specific. Moreover, it suggests that results cannot be easily generalized to study areas which are different from the analysed one.

Table 1 shows that car sharing users tend to be young (Becker et al., 2017a), in particular 25-35 years old (Shaheen and Martin, 2010), with high educational level (Clewlow, 2016). Moreover, car sharing seems to be adopted by both men and women, even if there is still a great attractiveness for potential female users (Alonso-Almeida, 2019). Future car sharing adopters are also full-time employed (Dias et al., 2017) or students (Le Vine et al., 2014a), owing a driving license (Sioui et al., 2012) and a public transport subscription (Kopp et al., 2015). Furthermore, users tend to live in dense urban areas (Kopp et al., 2015), where there is a high public transport Level Of Service (Becker et al., 2017b). In addition, car sharing adopters live in households with high income (Efthymiou and

Antoniou, 2016) and few owned cars (Martin et al., 2010). Other variables confirmed that the private car has a negative effect on car sharing adoption, such as the ratio between the number of members and cars in the household (de Luca and Di Pace, 2015), the frequency of use of private cars (Nobis, 2006), the presence of private car park near home (Ceccato and Diana, 2018) and the symbolic value of car (Kim et al., 2017b). Furthermore car sharing adopters tend to frequently use sustainable modes, such as public transport (Kim et al., 2017a) and non-motorized modes (Efthymiou et al., 2013), indeed environmental awareness is often observed among users (Millard-Ball et al., 2005) and electric shared vehicles are preferred (Zoepf and Keith, 2016). Finally, diffusion of technology seems to have a positive effect on the car sharing adoption (Shaheen and Martin, 2010).

On the other hand, several authors analysed the propensity to use car sharing focusing on a particular trip, therefore also trip-specific variables were included in Table 1. As expected, car sharing in-vehicle travel time, distance, cost (Becker et al., 2017b), and walking time to reach the nearest available vehicle (Zhou and Kockelman, 2011) have a negative effect on the choice. Furthermore, the majority of authors reported that car sharing is mostly used for discretionary trips (Kim et al., 2015).

Some authors analysed the variables affecting the choice to use car sharing by distinguishing various service models (Ciari et al., 2015). In this way, the effect of considered factors is different. For instance, Becker et al. (Becker et al., 2017a) compared characteristics of user groups of both Round-trip and One-way car sharing services. Furthermore, the propensity to use these two services was estimated also by Yoon et al. (Yoon et al., 2017) using Stated-preferences experiments. Moreover, after the increasing of environmental awareness and sustainability targets, several authors focused on the adoption of shared electric vehicles (Burghard and Dütschke, 2019; Cartenì et al., 2016).

Table 1. Variables affecting the use of car sharing: results from previous researches

Variables	Effect	Authors
Socio-economic - Individual level		
Age	Negative	(Alonso-Almeida, 2019; Becker et al., 2017a; Burghard and Dütschke, 2019; Ceccato and Diana, 2018; Coll et al., 2014; Dias et al., 2017; Martin and Shaheen, 2011a; Millard-Ball et al., 2005; Nobis, 2006; Paundra et al., 2017; Rotaris and Danielis, 2018; Vinayak et al., 2018; Wang et al., 2012)
	Positive	(Carroll et al., 2017; Cervero et al., 2007; de Luca and Di Pace, 2015; Kim et al., 2015) FF: (Yoon et al., 2017)
	Unspecified	(Acheampong and Siiba, 2019; Ciari et al., 2015, 2014; Cooper et al., 2000);
	Specific	+[26-35]: (Efthymiou, 2014; Efthymiou and Antoniou, 2016) +[20-59]: (Habib et al., 2012; Morency et al., 2012) +[18-64]: (Heilig et al., 2017) +[20-39]: (Kortum and Machemehl, 2012), (Sioui et al., 2012) +[25-39]: (Lane, 2005) +[25-35]: (Martínez et al., 2017) +[18-34]: (Perboli et al., 2017) +[20-35]: (Shaheen and Martin, 2010) +[25-44]: (Morsche et al., 2019) +[25-45]: (Cartenì et al., 2016) +[25-34]: (Shaheen et al., 2018) -(mean centred: 41.97): (Juschten et al., 2017) -[15-45]: (Wagner et al., 2016, 2015)
Gender	Male	(Acheampong and Siiba, 2019; Becker et al., 2017a; Carroll et al., 2017; Cartenì et al., 2016; Ceccato and Diana, 2018; Coll et al., 2014; Firnkorn and Müller, 2012; Habib et al., 2012; Juschten et al., 2017; Kim et al., 2017a; Morency et al., 2012; Perboli et al., 2017; Shaheen et al., 2018; Yoon et al., 2017)
	Female	(Burghard and Dütschke, 2019; Cervero, 2003; Cervero and Tsai, 2004; Coll et al., 2014; de Luca and Di Pace, 2015; Heilig et al., 2017; Kim et al., 2015; Martin and Shaheen, 2011a; Millard-Ball et al., 2005; Nobis, 2006; Vinayak et al., 2018; Zheng et al., 2009)
	Unspecified	(Alonso-Almeida, 2019; Ciari et al., 2015, 2014; Paundra et al., 2017)
Married	Positive	(Efthymiou, 2014; Efthymiou and Antoniou, 2016)

Educational level	Positive	(Becker et al., 2017a; Burghard and Dütschke, 2019; Carroll et al., 2017; Celsor and Millard-Ball, 2007; Ciari and Axhausen, 2012; Clewlow, 2016; Coll et al., 2014; Cooper et al., 2000; Dias et al., 2017; Juschten et al., 2017; Kim et al., 2017a; Kopp et al., 2015; Lane, 2005; Martin and Shaheen, 2011a; Millard-Ball et al., 2005; Nobis, 2006; Shaheen et al., 2018; Shaheen and Martin, 2010; Vinayak et al., 2018; Wang et al., 2012)
	Negative	(Acheampong and Siiba, 2019; Wagner et al., 2016, 2015)
	Unspecified	(Ciari et al., 2015, 2014)
Employment status	Positive	(Becker et al., 2017a; Carroll et al., 2017; Cartenì et al., 2016; Dias et al., 2017; Kim et al., 2015; Sioui et al., 2012; Vinayak et al., 2018)
	Negative	(Nobis, 2006)
	Unspecified	(Ciari et al., 2015, 2014)
	Specific	+[Student]: (Le Vine et al., 2014a; Perboli et al., 2017; Rotaris and Danielis, 2018; Zheng et al., 2009) -[Student]: (Zhou and Kockelman, 2011) +[Unemployed]: (Rotaris and Danielis, 2018)
Driving licence	Positive	(Acheampong and Siiba, 2019; Dias et al., 2017; Morsche et al., 2019; Rotaris and Danielis, 2018; Sioui et al., 2012; Winter et al., 2017; Yoon et al., 2017)
	Negative	(Carroll et al., 2017)
Public transport subscription	Positive	(Becker et al., 2017a; Ceccato and Diana, 2018; Cooper et al., 2000; Heilig et al., 2017; Juschten et al., 2017; Kopp et al., 2015; Yoon et al., 2017)
	Negative	(Martínez et al., 2017)
Socio-economic - Household level		
Income	Positive	(Acheampong and Siiba, 2019; Becker et al., 2017a; Ceccato and Diana, 2018; Clewlow, 2016; Cooper et al., 2000; Efthymiou et al., 2013; Juschten et al., 2017; Kim et al., 2017a; Kopp et al., 2015; Lane, 2005; Martin and Shaheen, 2011a; Millard-Ball et al., 2005; Nobis, 2006; Shaheen and Martin, 2010; Vinayak et al., 2018) FF: (Yoon et al., 2017)
	Negative	(Cervero et al., 2007; Ciari and Axhausen, 2012; Coll et al., 2014; Dias et al., 2017; Kim et al., 2015; Kortum and Machemehl, 2012; Wagner et al., 2016, 2015; Wang et al., 2012; Zhou and Kockelman, 2011) RT: (Yoon et al., 2017)
	Unspecified	(Efthymiou, 2014; Efthymiou and Antoniou, 2016)
Household size	Positive	(Burghard and Dütschke, 2019; Ciari and Axhausen, 2012)

	Negative	(Ceccato and Diana, 2018; Celsor and Millard-Ball, 2007; Cooper et al., 2000; Kim et al., 2017a; Kortum and Machemehl, 2012; Lane, 2005; Millard-Ball et al., 2005)
	Unspecified	(Ciari et al., 2015, 2014)
	Specific	+[Single]: (Kim et al., 2017b) +[2]: (Sioui et al., 2012), (Efthymiou et al., 2013) +[4 members]: (Perboli et al., 2017)
Number of children	Positive	(Carroll et al., 2017; Coll et al., 2014; Rotaris and Danielis, 2018; Sioui et al., 2012)
	Negative	(Dias et al., 2017; Kim et al., 2017a; Namazu et al., 2018; Vinayak et al., 2018)
Number of workers	Positive	(Ceccato and Diana, 2018; Namazu et al., 2018)
	Negative	-
Number of owned cars	Positive	(Paundra et al., 2017) RT: (Yoon et al., 2017)
	Negative	(Acheampong and Siiba, 2019; Becker et al., 2017a; Burghard and Dütschke, 2019; Catalano et al., 2008; Ceccato and Diana, 2018; Celsor and Millard-Ball, 2007; Clewlow, 2016; Cooper et al., 2000; Dias et al., 2017; Juschten et al., 2017; Kopp et al., 2015; Lane, 2005; Martin and Shaheen, 2011a; Millard-Ball et al., 2005; Murphy, 2016; Namazu et al., 2018; Nobis, 2006; Shaheen and Martin, 2010; Sioui et al., 2012; Vinayak et al., 2018; Zhou and Kockelman, 2011) FF: (Yoon et al., 2017)
	Unspecified	(Ciari et al., 2015, 2014)
	Specific	+[1]: (Efthymiou, 2014; Efthymiou and Antoniou, 2016) +[2]: (Perboli et al., 2017)
Number of owned bicycles	Positive	(Becker et al., 2017a; Coll et al., 2014; Juschten et al., 2017)
	Negative	(Cervero et al., 2007)
Number of owned motorbikes	Positive	(Ceccato and Diana, 2018)
	Negative	-
Drivers/car	Positive	(Coll et al., 2014; Juschten et al., 2017)
	Negative	(Rotaris and Danielis, 2018)
Household members/car	Positive	(de Luca and Di Pace, 2015; Heilig et al., 2017)
	Negative	-
Private parking near home	Positive	-
	Negative	(Ceccato and Diana, 2018; Juschten et al., 2017; Martínez et al., 2017)
Working location	Unspecified	(Carroll et al., 2017; Ciari et al., 2015, 2014) +[Near home]: (Martin and Shaheen, 2011a) -[Out of home]: (Kortum and Machemehl, 2012)
Trip characteristics		
Car sharing cost	Positive	(Carroll et al., 2017; Paundra et al., 2017)
	Negative	(Becker et al., 2017b; Cartenì et al., 2016; Catalano et al., 2008; Ciari and Axhausen, 2012;

		de Luca and Di Pace, 2015; Kim et al., 2017a; Le Vine et al., 2014b, 2014a; Martínez et al., 2017; Millard-Ball et al., 2005; Morsche et al., 2019; Rotaris et al., 2019; Winter et al., 2017; Yoon et al., 2017; Zheng et al., 2009; Zoepf and Keith, 2016)
	Unspecified	(Ciari et al., 2015, 2014)
Car sharing travel time	Positive	(Carroll et al., 2017)
	Negative	(Becker et al., 2017b; Cartenì et al., 2016; Catalano et al., 2008; Cervero et al., 2007; Ciari and Axhausen, 2012; de Luca and Di Pace, 2015; Efthymiou, 2014; Efthymiou and Antoniou, 2016; Kim et al., 2017a; Le Vine et al., 2014b; Martínez et al., 2017; Morsche et al., 2019; Wagner et al., 2016, 2015)
	Unspecified	(Ciari et al., 2015, 2014)
Car sharing walking time	Positive	(Winter et al., 2017) RT: (Yoon et al., 2017)
	Negative	(Ciari and Axhausen, 2012; de Luca and Di Pace, 2015; Kim et al., 2017a; Le Vine et al., 2014a; Martínez et al., 2017; Rotaris et al., 2019; Zheng et al., 2009; Zhou and Kockelman, 2011) FF: (Yoon et al., 2017)
	Unspecified	(Ciari et al., 2015, 2014)
Car sharing distance	Positive	-
	Negative	(Becker et al., 2017b; Juschten et al., 2017; Shaheen and Martin, 2010; Wagner et al., 2016, 2015; Zoepf and Keith, 2016)
	Unspecified	(Ciari et al., 2015, 2014)
	Specific	+[More than 25 km]: (Rotaris and Danielis, 2018)
Car sharing walking distance	Specific	-[Less than 1 km, SB]: (Heilig et al., 2017) +[Less than 1 km, FF]: (Heilig et al., 2017)
Parking cost	Positive	(Juschten et al., 2017)
	Negative	(Ciari and Axhausen, 2012; Paundra et al., 2017)
Trip purpose	Specific	+[Leisure]: (Ciari and Axhausen, 2012; Kim et al., 2015; Millard-Ball et al., 2005) +[Home-based]: (de Luca and Di Pace, 2015) +[Non-working]: (Cartenì et al., 2016) -[Return home]: (Sioui et al., 2012)
	Unspecified	(Le Vine et al., 2014b)
Location of origin or destination	Unspecified	(Becker et al., 2017b; Ciari et al., 2015, 2014; Heilig et al., 2017; Kopp et al., 2015)
Weather conditions	Specific	+[Cold and Rainy]: (Becker et al., 2017b) +[Good]: (Winter et al., 2017)
Departure time	Specific	+[Morning peak period, RT]: (Yoon et al., 2017)
Electric vehicle	Positive	(Cartenì et al., 2016; Rotaris et al., 2019; Zoepf and Keith, 2016)
Spatial information (e.g. transit accessibility, number of shared vehicles, residential density)		(Becker et al., 2017a, 2017b; Celsor and Millard-Ball, 2007; Ciari et al., 2015, 2014; Coll et al., 2014; de Luca and Di Pace, 2015; Habib et al., 2012; Kopp et al., 2015; Kortum and Machemehl,

		2012; Morency et al., 2012; Morsche et al., 2019; Namazu et al., 2018; Rotaris and Danielis, 2018; Vinayak et al., 2018; Wagner et al., 2016; Wang et al., 2012; Yoon et al., 2017; Zhou and Kockelman, 2011)
Travel habits		
Frequency of car	Positive	(de Luca and Di Pace, 2015; Kim et al., 2017a)
	Negative	(Kopp et al., 2015; Millard-Ball et al., 2005; Nobis, 2006; Paundra et al., 2017; Shaheen and Martin, 2010; Sioui et al., 2012)
Frequency of public transport	Positive	(Celsor and Millard-Ball, 2007; Clewlow, 2016; Cooper et al., 2000; Kim et al., 2017a; Lane, 2005; Murphy, 2016; Shaheen and Martin, 2010)
	Negative	(Coll et al., 2014; Nobis, 2006)
Frequency of non-motorized modes	Positive	(Celsor and Millard-Ball, 2007; Clewlow, 2016; Coll et al., 2014; Cooper et al., 2000; Efthymiou et al., 2013; Kopp et al., 2015; Lane, 2005; Shaheen and Martin, 2010)
	Negative	(Sioui et al., 2012)
Personal awareness and habits		
Smartphone	Positive	(Acheampong and Siiba, 2019; Dias et al., 2017; Shaheen and Martin, 2010; Vinayak et al., 2018)
	Negative	-
Environmental awareness	Positive	(Acheampong and Siiba, 2019; Efthymiou, 2014; Efthymiou et al., 2013; Efthymiou and Antoniou, 2016; Millard-Ball et al., 2005; Rotaris and Danielis, 2018; Winter et al., 2017; Zheng et al., 2009)
	Negative	(Kim et al., 2017b)
Symbolic value of car	Positive	(Nobis, 2006)
	Negative	(Kim et al., 2017b; Zheng et al., 2009)

Notes: + and – indicate a positive and negative effect, respectively. FF: Free-floating, RT: Round-trip

2.4. Relationship with other modes

Due to the growing diffusion of car sharing services, understanding the relationship between this mode and other travel means is a key aspect to forecasting models (Dias et al., 2017). Moreover complementarity and substitution patterns were analysed to help transportation planners and policy makers in managing the whole range of mobility options (Welch et al., 2018). In addition, previously described benefits can be effective only if car sharing is able to attract private car drivers and, therefore, if it does not compete with other existing sustainable modes (such as public transport, bike and walking) (Sprei et al., 2018; Welch et al., 2018). For these reasons, many authors studied different causes and aspects of these relationships, in particular between car sharing and public transport. Through modelling approaches or statistical analysis of mobility surveys, several authors observed a complementary pattern.

2.4.1. Public transport

Becker et al. (Becker et al., 2017a, 2017c) found a link between public transport pass owners and propensity to join and use car sharing in Basel, Switzerland, therefore they concluded that car sharing complement public transport. Similarly, Zoepf and Keith (Zoepf and Keith, 2016) derived the same statement analysing data from a survey administered to members of Zipcar in North America. Furthermore, many authors provided different explanations to support this view. For instance, car sharing can be adopted for "first and last mile" connections, i.e. it can provide the link between the station or the stop of public transport, and the final destinations of travellers (Lagadic et al., 2019; Le Vine and Polak, 2019; Shaheen and Chan, 2016; Shaheen and Wright, 2001). According to this perspective, car driving trips are substituted by a combination of car sharing and public transport (Lane, 2005). On the other hand, car sharing can provide access to transit stations and stops in areas where public transport is not enough widespread (Barth and Shaheen, 2002; Cooper et al., 2000; Kopp et al., 2013; Millard-Ball et al., 2005; Murphy, 2016; Shaheen and Wright, 2001), e.g. in rural areas (Rotaris and Danielis, 2018). In particular, analysing booking requests of a car sharing operator in Shanghai, China, Hu et al. (Hu et al., 2018a) estimated that car sharing was appealing when the distance from a bus stop ranges from 1.2 to 2.4 km. In these two ways, transit accessibility is increased (Coll et al., 2014; Rotaris and Danielis, 2018). From the opposite perspective, public transport can give easy access to shared vehicles to travellers living far from car sharing locations (Millard-Ball et al., 2005). In addition, car sharing can complement public transport from a temporal perspective. In particular, it can be used when public transport is less frequent (Murphy, 2016; Shaheen and Wright, 2001), e.g. in off-peak periods or during weekends (Costain et al., 2012b; de Luca and Di Pace, 2015; Martínez et al., 2017; Millard-Ball et al., 2005). Moreover, it can ensure a continuous service when public transport is not guaranteed (de Luca and Di Pace, 2015; Murphy, 2016). Furthermore, car sharing can be adopted for particular needs not covered by public transport (Kopp et al., 2013). For instance, discretionary trips are usually difficult to be accommodated by transit, due to their uneven timing and destinations; on the contrary, car sharing can provide the necessary flexibility and convenience for this type of trips, thus complementing public transport, even according to this perspective (Cooper et al., 2000; Kopp et al., 2013; Wang et al., 2017). Furthermore, a complementary usage is observed when travellers have to carry heavy loads (de Lorimier and El-Geneidy, 2012; Kopp et al., 2013; Millard-Ball et al., 2005). Because of this relationship of complementarity between car sharing and public transport, many authors observed an increased use of transit by car sharing members (as reported in the previous section). Therefore a better integration between these two transport modes can be advantageous for both of them, providing new potential users (Firnkorn and Müller, 2011; Gordon-Harris, 2016; Huwer, 2004; Mounce and Nelson, 2019; Shaheen and Chan, 2016; Welch et al., 2018). This integration can be realized through a joint price structure, unified ticket/subscription, or the creation of mobility points connecting car sharing parks with transit stops and stations (Barth and Shaheen, 2002; Huwer, 2004).

On the contrary, some authors highlighted a relationship of substitution between car sharing and public transport. In particular, analysing Car CityShare in San Francisco, Cervero et al. (Cervero et al., 2007) reported that car sharing was used as a substitute of public transport for systematic (work and school), business and medical trips. Using an agent-based simulation of car sharing in Lisbon, Portugal, Martinez et al. (Martínez et al., 2017) found that car sharing was competitive in terms of travel time respect to public transit. Therefore the former could substitute the latter both for short trips, for which the latter would be penalized by access and waiting time, and for long trips, for which the probability to have transfers and related waiting time increases. Similarly, Sprei et al. (Sprei et al., 2018) studied usage patterns of Free-floating operators in 12 cities in Europe and United States. The authors showed that car sharing could compete with public transport in terms of trip duration and they estimated a time gain between 10 and 30 minutes, on average.

On the other hand, other authors found ambiguous relationships (Clewlow, 2016). For instance, Martin and Shaheen (Martin and Shaheen, 2016) showed that car2go members in Ulm considered the service both as substitution and complement to public transport, indeed the majority of them did not report any changes in transit usage. Stillwater et al. (Stillwater et al., 2009) analysed car sharing reservations of an operator in United States. In particular, they obtained a positive relationship between car sharing and local light rail public transport, but a negative relationship with regional rail transit, highlighting that car sharing complemented the former and substituted the latter. The authors reported two explanations. First, accessibility provided by regional transit made car sharing less attractive, since it reduced the need for other long trips. Lastly, self-selection might have caused it, i.e. people intentionally decided to live near rail stations, in order to drive less.

In addition, some authors reported different impacts according to the car sharing operational service model. For instance, Becker et al. (Becker et al., 2017c) considered separately One-way Free-floating and Station-based car sharing services in Switzerland. In particular, they reported that Station-based car sharing, not being used for daily trips, could complement public transit. On the other hand, Free-floating was considered the most suitable alternative to public transport due to its flexibility (Becker et al., 2017b). In particular, it complemented public transport (Becker et al., 2017a) during the night, in bad weather conditions and for discretionary trips (Becker et al., 2017b). Therefore Becker et al. (Becker et al., 2017a) concluded that Free-floating increases the use of public transport and non-motorized trips. Similarly, using rental data of car sharing in Berlin, Germany, Wagner et al. (Wagner et al., 2016, 2015) observed that Free-floating could complement public transport for short urban trips. On the contrary, adopting an agent-based simulator in Berlin, Ciari et al. (Ciari et al., 2014) observed that, unlike Station-based, Free-floating car sharing could substitute public transport, since it was found to be suitable even for commuting trips.

Concerning the difference between One-way and Round-trip car sharing, Le Vine et al. (Le Vine et al., 2014b) modelled car sharing impacts in London. In particular, they highlighted that the former was mainly used for commuting trips, whereas the latter for discretionary purposes; therefore they noted that One-way could substitute public transport and Round-trip could complement it. On the contrary, Namazu et al. (Namazu and Dowlatabadi, 2018) reported that, in Vancouver, only One-way car sharing was used as a complement to public transport. Similarly, Shaheen and Chan (Shaheen and Chan, 2016) argued that One-way car sharing can better complement public transit, since it provides great flexibility for first and last mile connections. On the contrary, Shaheen et al. (Shaheen et al., 2015) noted that car sharing operators considered One-way as a substitute of public transport and Round-trips as a complement.

2.4.2. Bike and walking

Most of the authors argued that car sharing complement both cycling and walking trips, since previous solo driving trips were substituted by multi-modal trips, which include these two active modes (Lane, 2005). Cooper et al. (Cooper et al., 2000) analysed travel behaviour of CarSharing Portland members and concluded that car sharing can complement walking and bike for activities that would be inconvenient to perform by these two modes (e.g. carrying heavy loads or for night travels). Similarly, in Lisbon, Martinez et al. (Martínez et al., 2017) estimated that car sharing outperformed walking in terms of travel time, therefore it complemented this mode for long trips (up to 3 km).

On the contrary, in the first and second year of City CarShare in San Francisco, Cervero (Cervero, 2003) and Cervero and Tsai (Cervero and Tsai, 2004) observed that some trips made by foot or bike were substituted by car sharing, due to the novelty and initial appeal of the service. However, in the fourth year, Cervero et al. (Cervero et al., 2006) found that members biked and walked more than non members.

On the other hand, Martin and Shaheen (Martin and Shaheen, 2016) found ambiguous results in the five North American cities analysed. In particular, in four cities, 20% of members reported to walk more frequently, whereas 10% to walk less. Moreover, in all cities the percentages of increasing or decreasing bike frequency were below 10%.

2.4.3. Taxi

Several authors argued that taxi is one of the main competitors of car sharing, since they share common characteristics (Millard-Ball et al., 2005), such as comfort, time saving (respect to public transport) and no parking needs (Efthymiou and Antoniou, 2016), even if with different costs (Martínez et al., 2017; Millard-Ball et al., 2005).

For instance, observing fares of taxi and car sharing in San Francisco, Millard-Ball et al. (Millard-Ball et al., 2005) reported that, while the latter was cost-effective for short duration trips, the former was cheaper for trips with short distance and long duration, since a shared car would be parked for a long time, increasing its cost. Moreover, analysing travel habits of car sharing members in seven cities in United States, Murphy et al. (Murphy, 2016) observed that car sharing was a substitute of taxi. Similarly, according to Efthymiou and Antoniou (Efthymiou and Antoniou, 2016) car sharing could compete with taxi for social activities in Athens, Greece. Martin and Shaheen (Martin and Shaheen, 2016) reported that car sharing members in all the five considered North American cities decreased the taxi usage after joining car sharing, with percentages ranging from 42% to 65%. Therefore the authors concluded that car sharing could substitute taxi. In Beijing, Yoon et al. (Yoon et al., 2017) showed that car sharing could compete with taxi, particularly when taxi fares were high. Analogously, using an agent-based simulator in Lisbon, Martinez et al. (Martínez et al., 2017) argued that car sharing could substitute taxi when the latter had greater costs. In particular during evening and night period, since only taxi has a night extra tariff, for short trips, due to the taxi initial charge, and for long trips, since the price per kilometre of car sharing is lower.

On the other hand, introducing car sharing in an agent-based simulator in Zurich, Switzerland, Ciari et al. (Ciari et al., 2015) estimated a negligible impact of car sharing on taxi.

2.4.4. Car sharing services

In several cities around the world, more than one car sharing operator with different service models is present. Therefore, each operational model can compete or complement with another one.

Ciari et al. (Ciari et al., 2014) analysed impacts of both One-way Free-floating and Station-based car sharing in Berlin, using an agent-based simulator. They found that the former was more suitable for commuting trips, whereas the latter was more used for leisure, because of the typical short duration of such trips. Therefore the authors concluded that the two car sharing services were complementary. In a later work on car sharing pricing schemes in Zurich, Ciari et al. (Ciari et al., 2015) derived the same thesis from two observations, considering One-way Free-floating and Round-trip Station-based services. Firstly, the number of Round-trips rentals was maximum when Free-floating had a half-price all day. Secondly, Free-floating could be used by travellers who did not find an available Round-trip shared vehicle. Similarly, Namazu et al. (Namazu and Dowlatabadi, 2018) argued that the same two service models were complementary, in Vancouver. In particular, since members of both services reported to buy a personal car after the termination of car sharing, the authors concluded that the two models complemented each other, providing different mobility services. This observation was supported by the maximum likelihood to share a vehicle obtained for members of both car sharing models.

Moreover, Jorge et al. (Jorge et al., 2015a) developed a method to optimize the use of both One-way and Round-trip models, depending on users' needs. They applied the implemented method to a high demand generator (i.e. an airport) in Boston, United States, obtaining an increase of the satisfied demand and of the profitability of the car sharing operator.

Furthermore, Shaheen et al. (Shaheen et al., 2015) administered a survey of 31 car sharing operators in the Americas. They reported that most of the interviewees (about 70%) considered One-way as a complement of Round-trip, about 20% viewed it as a competitor and the remaining part both as competitor and complement.

2.5. Identification of the car sharing potential impacts

Many authors observed and analysed several positive impacts of car sharing, which are partly due to changes in the modal split after the introduction of the service. The most frequently reported effects are: the reduction of car ownership, decreasing fuel consumption and greenhouse gas emissions, increase in the use of sustainable alternative travel modes (e.g. public transport, bike and walking), the saving of transportation costs borne by travellers, the reduction of Vehicle Miles Travelled (VMT) and the decrease of parking space occupied by cars (Barth and Shaheen, 2002; Cohen and Shaheen, 2016). Overall, the estimation of these effects leads to results that are site-specific (Lane, 2005), i.e. they differ among the countries (Martin et al., 2010; Shaheen and Cohen, 2007) and the cities within the same country (Jakobsson Bergstad et al., 2018; Martin and Shaheen, 2016). These differences might be due to attributes of both the demand side, such as socio-economic characteristics and mobility styles of users (Ramos et al., 2020), and the offer side, such as the types of car sharing business models (Becker et al., 2017a). For this reason, impacts in a specific study area are unlikely to be generalizable or transferable to other zones (Lane, 2005), and a global magnitude of the impacts cannot be identified.

2.5.1. Reduction of car ownership

The adoption of car sharing introduces a shift in the cost structure of driving: from fixed cost, typical of owned cars and often misperceived, to variable cost (Cohen and Shaheen, 2016; Martin and Shaheen, 2011a), even from a user perspective. Therefore, after becoming aware of the cost of driving, users choose their transport mode more rationally (Ceccato and Diana, 2018; Cervero et al., 2007, 2006; Cervero and Tsai, 2004; Huwer, 2004; Morency et al., 2015). This leads to changes in travel habits, including decisions to sell owned cars, delay or forgo the purchase of a vehicle (Cohen and Shaheen, 2016). However, after joining car sharing, non car owners can experience the flexibility of private mobility, in this way car sharing might induce them to buy a private car (Namazu et al., 2018). Despite this drawback, many authors reported a reduction of car ownership after joining car sharing. The link between these two elements is uneven since it might change according to socio-economic characteristics and travel habits of users. For instance, car owners and non car owners have different approaches towards car sharing, since the formers tend to overuse their cars, in order to take benefits from the car that they bought and to amortise the related fixed cost (Coll et al., 2014).

Many authors estimated changes in car ownership after the introduction of car sharing, however different results were obtained according to the period in which the analysis was carried out, the car sharing business model and the study area. As regards changes over time of the impact of car sharing on car ownership, most of the authors did not explicit this analysis in their works, since they considered only a specific time period. Nevertheless, Namazu et al. (Namazu et al., 2018) highlighted the difference between current and potential members of car sharing service in the Vancouver Metropolitan region (Canada) in terms of both socio-economic characteristics and use of the service. In particular, they observed that the formers owned few cars and they used the service as an alternative to private cars, whereas the latter were households with older persons and fewer wage earners. Moreover, many changes in car ownership could be due also to other long term decisions, such as changes in residential work location, or changes in lifestyle, e.g. due to an increasing size of the household (Jain et al., 2020). Therefore, the impacts of car sharing on vehicle ownership are likely to have a different level in the future (Millard-Ball et al., 2005; Namazu et al., 2018). This conclusion was confirmed by some results, although in another country, by Cervero et al. (Cervero, 2003; Cervero et al., 2007, 2006; Cervero and Tsai, 2004) who analysed impacts of City CarShare service in San Francisco (United States), by administering a travel survey one year, two years and four years after the introduction of the car sharing service. In particular, they found that after an initial decreasing rate of vehicle ownership among members, the degree of car shedding levelled off (Cervero et al., 2007). In particular, in the second wave, 29.1% of members and 8% of non-members reduced the number of owned cars, whereas, in the third wave, these percentages were 24.2% for members and 24.5% for non-members. Similarly, Becker et al. (Becker et al., 2018) administered a survey in Basel (Switzerland) in two waves. The first one was carried out six months after the launch of the car sharing service, whereas the second one was administered one year later. The Authors estimated the reduction of car ownership respect to a control group of non-members, reporting that members stated that they would decrease their car ownership level by 0.13 cars, respect to the control group, however results of the second wave highlighted that the current reduction was by 0.08 cars. This suggests that the impact of car sharing on car ownership might change over time (Firnkorn and Shaheen, 2016).

Few authors estimated different effects of car sharing on vehicle ownership according to the business model of the considered car sharing service. Le Vine et al. (Le Vine et al., 2014b) evaluated the potential impact of introducing an One-way car sharing system in London, where a Round-trip service already exists. In particular, they estimated that the latter produced a reduction of owned cars by 3.5%, whereas the former was forecasted to have an impact of only an additional 0.5%, since most of the person had already given up their personal vehicles (Le Vine et al., 2014b). Similarly, Namazu and Dowlatabadi (Namazu and Dowlatabadi, 2018) analysed effects of both One-way (Free-floating) and Two-way car sharing systems, by administering a travel survey to members in Vancouver (Canada). The authors found that both the services lead to a reduction of car ownership, however, because of different socio-economic characteristics and usage of the two groups of respondents, the decreasing rate of private car is not the same. In particular, they observed that One-way car sharing is adopted as a substitute of private car, on the other hand, Two-way is used as a complement to all travel modes; therefore, Two-way members were five times more likely to shed their personal car, rather than One-way users. Furthermore, the car ownership rate of members of the One-way service shifted from 1.08 cars per household after joining to 0.98 afterwards, whereas, for members of the Two-way system, the rate switched from 0.68 to 0.36. Other authors compared the effects of Station-based and Free-floating business models. Giesel and Nobis (Giesel and Nobis, 2016) studied the impacts of such systems in Berlin and Munich (Germany). They pointed out that car ownership of the members of the two services was different; specifically, 72% of Station-based members lived in zero-car household, whereas 43% of Free-floating users lived in household with no cars. Moreover, they found that about 15% of Station-based customers gave up a car due to car sharing membership, but only 7% of Free-floating customers shed a car because of car sharing participation. Similarly, in a study about existing One-way car sharing services in Basel (Switzerland) Becker et al. (Becker et al., 2017a) found that 8% of Free-floating car sharing members and 19% of Station-based car sharing members reported that they would buy an extra car if the car sharing service were not be available any more.

On the other hand, different impacts were evaluated according to the location of the study area. In particular, these differences might be due to the characteristics of the city and planning (e.g. road pricing) (Habibi et al., 2017), the diffusion of other travel modes (Habibi et al., 2017), the type and characteristics of the provided car sharing service (e.g. pricing scheme) (Sprei et al., 2018), and the degree of saturation of car market in the country (Firnkorn and Shaheen, 2016). However, it is difficult to find a common impact on car ownership within a country, since results are site-specific (Lane, 2005; Sioui et al., 2012); for this reason, different authors estimated different effects, which cannot be transferred to other regions (Lane, 2005). For instance, analysing impacts reported in several previous works, Millard-Ball (Millard-Ball et al., 2005) evaluated that Europe and North America shared similar percentages of members who gave up a car after joining the service; these values were 22% for Europe and 21% in North America, on average. On the other hand, Shaheen and Cohen (Shaheen and Cohen, 2007) reported that the number of reduced owned cars after the introduction of car sharing ranged from 4 to 10, in Europe, and from 6 to 23, in North America. Furthermore, the percentage of members deciding to forgo a vehicle purchase after joining a service ranged from 23% to 26%, in Europe, and from 12% to 68%, in North America. These differences might be due to the higher car ownership rate in North America, rather than in Europe, therefore the potential number of persons deciding to shed a car might be higher (Shaheen and Cohen, 2007). Martin et al. (Martin et al., 2010) used a before-and-after survey to assess car ownership changes in North American car sharing members. In particular, they observed that the average number of private car per household switched from 0.55 before joining car sharing to 0.29 afterwards; whereas, in Canada, the average shifted from 0.31 to 0.13.

As regards studies carried out in Europe, Firnkorn and Müller (Firnkorn and Müller, 2011) studied car sharing impacts in Ulm, Germany, and concluded that about 14% of members might reduce their car ownership. Later, the same authors (Firnkorn and Müller, 2012) estimated that each existing shared car in Ulm substituted 2.3-10.3 private cars, but it could potentially replace up to 19.2 individual vehicles. Le Vine and Polak (Le Vine and Polak, 2019) collected data on members characteristics and travel habits, three months after the introduction of One-way car sharing in London (United Kingdom). Results indicated that 30% of respondents stated that they forwent purchasing a private car after joining car sharing, 4% decided to dispose a car and about 2% declared that they will sell a personal car. In Basel, Becker et al. (Becker et al., 2018) estimated that Free-floating car sharing can potentially reduce the level of car ownership by 24%, which corresponds to a reduction of 0.06 vehicles per household.

Considering works developed on North American countries, analysing data from a survey of car sharing members in United States and Canada, Millard-Ball et al. (Millard-Ball et al., 2005) reported a change of about 14.9 private cars per shared vehicle. After one year of the introduction of PhillyCarShare service in Philadelphia, Pennsylvania (Unites Stated), Lane (Lane, 2005) reported that each shared car removed 22.8 from the roads, on average. During the introduction of Austin CarShare in Austin, Texas (Unites States) Zhou and Kockelman (Zhou and Kockelman, 2011) administered a travel survey to the population, and they estimated that about 21% of the sample would eventually sell a personal vehicle, if they were members and a shared vehicle were available near their home. Moreover Sioui et al. (Sioui et al., 2012) evaluated car sharing users characteristics in Montreal (Canada), showing that their car ownership rate was lower rather than the one of non members (0.13 cars per household against 0.89). Stasko et al. (Stasko et al., 2013) evaluated impacts of car sharing in a university setting in Ithaca, New York (United States), reporting a reduction of 15.3 vehicles per shared car. Morency et al. (Morency et al., 2015) quantified the number of shared cars that would be necessary to meet the same travel demand performed by private vehicles. In particular, they estimated that the fleet size of shared car should be between 48% and 59% of the current number of private vehicles in order to satisfy the same demand in Montreal (Canada). Travel behaviour and car ownership of members and non members in the San Francisco Bay Area (United States) were analysed by Clewlow (Clewlow, 2016), who found that users living in urban areas owned less vehicles than non users (0.58 vehicles per household against 0.96). Martin and Shaheen (Martin and Shaheen, 2016) administered a survey to car2go members in 5 cities in Canada and United Stated. Results showed that between 2% and 5% of users sold a private car after joining the service and 7% to 10% of interviewees decided not to purchase a vehicle. Furthermore the authors estimated that each car2go car could replace from 7 to 11 personal cars. Mishra et al. (Mishra et al., 2015) used the California Household Travel Survey to analyse impacts of car sharing on travel behaviour and car ownership of users in the San Francisco Bay Area, addressing self-selection bias. In particular they found that car sharing members significantly owned less vehicles rather than non members with similar socio-economic, dwelling and job location characteristics. In a later work the authors (Mishra et al., 2017) adopted the same dataset to address self-selection and simultaneity bias. Moreover they estimated that car sharing contributes to remove one vehicle every six households with at least one car sharing member.

2.5.2. Decreasing parking space

Many authors analysed the link between the decreasing car ownership and the reduction of parking demand (Efthymiou et al., 2013; Stasko et al., 2013). These studies are based on the observation that private vehicles are parked for more than 95% of the time (Jorge and Correia, 2013; Morency et al., 2015; Mounce and Nelson, 2019). Parking spaces in cities reduce the space for other land uses (Stasko et al., 2013), especially for urban development (Millard-Ball et al., 2005). Moreover parking spaces lower the storm water runoff (Millard-Ball et al., 2005). Furthermore parking surface is often limited, leading to high cost of usage (Stasko et al., 2013). However the increasing availability of parking space provided by car sharing might have also negative effects, since it can make the use of private car more attractive (Mounce and Nelson, 2019). Furthermore, the quantification of these impacts is complex since effects are site specific (Stasko et al., 2013); in particular car sharing benefits on parking demand are not effective if substituted private vehicles were parked in garages (Stasko et al., 2013). Analysing car sharing parking impacts at a building scale in Toronto, Canada, Engel-Yan and Passmore (Engel-Yan and Passmore, 2013) estimated that buildings with dedicated shared vehicles lowered parking space by 50% respect to those without dedicated shared cars. Furthermore Stasko et al. (Stasko et al., 2013) studied parking reduction after the introduction of car sharing in Ithaca, highlighting different reduction rates according to the period of analysis. For instance, they found that on weekday, nights and weekend car sharing might substitute 4.7 private cars parked on the street.

2.5.3. Increase use of sustainable modes

Changes in modal split of car sharing members are often reported after the adoption of car sharing (Clewlow, 2016; Lane, 2005), since the cost structure of car sharing encourages users to compare different travel modes and destinations for their daily activities (Coll et al., 2014). In particular, they are prompted to look for means which are alternative to private car (Namazu and Dowlatabadi, 2018), even complementing car sharing with other sustainable modes (e.g. public transit, bike and walking). Moreover being multimodal was found to be a positive factor to join car sharing (Nobis, 2006), suggesting that multimodality tend to be a characteristic of car sharing members. However, the relationship and related impacts of car sharing on alternative modes are controversial, especially for public transport (Clewlow, 2016; Stillwater et al., 2009). This ambiguity is often due to socio-economic characteristics of users, their travel habits and site-specific variables (Ceccato and Diana, 2018). For instance, considering public transport, members more oriented to a car use might adopt car sharing as a substitute for public transit, on the contrary others might complement it with car sharing (Mounce and Nelson, 2019).

On average, several authors stated that car sharing can increase the use of sustainable alternative modes, but some others found the opposite, like, Martin and Shaheen (Martin and Shaheen, 2011a) who reported that, after joining car sharing, in North America, users slightly lowered the use of public transport, but they increased the use of bike, by 7%, and walking, by 2%. Differences might be due to the study area (Lane, 2005) and to the business model of the existing car sharing services (Becker et al., 2017a), as explained in the previous paragraphs. Among authors showing increasing usages in

North American cities, Cooper et al. (Cooper et al., 2000) evaluated the effect of CarSharing Portland in Portland, Oregon (United States), two years after the launch, and reported that members increased the use of public transport by 14%, the use of bike by 10% and walking by 25%. Lane et al. (Lane, 2005) obtained similar results in Philadelphia (United States), where car sharing adopters increased public transit usage by 18%, bike by 8% and walking by 19%, one year after the introduction of the service. Furthermore Millard-Ball et al. (Millard-Ball et al., 2005) reported that about 40% of interviewed members in United States took transit more and 37% walked more. Sioui et al. (Sioui et al., 2012) evaluated that car sharing members used public transport 55% more often than non members in Montreal (Canada). Mishra et al. (Mishra et al., 2015) developed a model for usage frequency of transit and non motorized modes, in the San Francisco Bay Area (United States); results indicated that car sharing members had a greater propensity to use more often public transport, bike and walking, if compared to non members. In a later work, the same authors (Mishra et al., 2017) found that car sharing effect on the usage frequency of previous modes was positive, even if statistically non significant. As regards the effect of the type of business model of car sharing services, Becker et al. (Becker et al., 2017a) evaluated the related impacts on travel habits of both Free-floating and Station-based systems in Basel (Switzerland). In particular, they found that most of the members of the second service type increased the use of public transport and non motorized modes, after joining car sharing, whereas an opposite effect was observed for Free-floating members.

2.5.4. Vehicle Miles Travelled reduction

Car ownership reduction implicates an overall decrease of Vehicle Miles Travelled (Cohen and Shaheen, 2016; Dill et al., 2019), considering the use of both private car and car sharing. In addition, car sharing adoption motivates drivers to use vehicles more appropriately (Morency et al., 2015), contributing to shorten trip distances (Huwer, 2004). For these reasons, many authors reported a VMT reduction, after the introduction of car sharing. However, other authors found the opposite, since, joining the service, non car owners increase their VMT (Cervero, 2003; Martin and Shaheen, 2011a; Millard-Ball et al., 2005; Namazu et al., 2018). Therefore the effect of car sharing on VMT can be positive only if the global balance of VMT is negative (Namazu et al., 2018). Impacts might be different because of site-specific characteristics, which might also change over time after the introduction of car sharing. As regards this last aspect, analysing City CarShare impacts after one year, Cervero et al. (Cervero, 2003) showed a decreasing of average VMT both for members and non members, even if these variations were not statistically significant (Cervero, 2003; Cervero et al., 2006). Then, at the end of the second year of the service, Cervero and Tsai (Cervero and Tsai, 2004) estimated that average VMT lowered by 2% for members and increased by 95% for non members. Finally, Cervero et al. (Cervero et al., 2007) reported that, from the first to the fourth year of the car sharing program, members decreased average VMT by 32%, whereas non members raised average VMT by 41%. These changes over time highlighted that car sharing promoted a rational travel behaviour, contributing to a shift to other sustainable modes (Cervero et al., 2006).

In Europe, Shaheen and Cohen (Shaheen and Cohen, 2007) estimated that VMT decreased from 28 to 45% per car sharing user, on average. In other countries, controversial results were found. For instance, after the introduction of PhillyCarShare in Pennsylvania (United States), Lane et al. (Lane, 2005) reported an increase of monthly VMT of 29.9 mi at maximum, for people gaining access to a car, whereas members giving up their personal vehicle decreased monthly VMT by 522 mi at maximum. Furthermore, in a study about car sharing in North America, Martin and Shaheen (Martin and Shaheen, 2011b) found an increase of VMT for carless household after joining the service, however the calculated global effect was a reduction of average VMT per year by 27% (43% if considering also distances that would have been driven in absence of car sharing). More recently, the same authors (Martin and Shaheen, 2016) analysed impacts of One-way Free-floating car2go in five North American cities, showing both an increasing and decreasing VMT among members. However the overall effect was a reduction of VMT per household ranging from 6% (in Calgary) and 16% (in Washington and Vancouver), with an average total reduction of 11%. Similarly, Cooper et al. (Cooper et al., 2000) showed that members of CarSharing Portland reduced their VMT by about 8%. Millard-Ball et al. (Millard-Ball et al., 2005) reported a reduction of about 63%. In a study about North American car sharing, Shaheen et al. (Shaheen et al., 2010) calculated a reduction of about 44% of VMT per member, even if it ranged from 7.6% to 80% (Shaheen et al., 2006). Moreover, Martin et al. (Martin et al., 2010) highlighted that average VMT per year for each shared car was less than 33% in United States and less than 13% in Canada, if compared to VMT of a household vehicle. Furthermore, in Montréal (Canada) Sioui et al. (Sioui et al., 2012) found that households joined car sharing used a car 3.7 less than others. Clewlow (Clewlow, 2016) reported that members living in suburban neighbourhood of San Francisco Bay Area (United States) drove 15.8 VMT per day on average, while non members drove 23.6 VMT per day.

2.5.5. Lowering emissions

Car sharing has also a positive impact on sustainability. In particular, the induced decrease of car ownership leads to a reduction of congestion and air pollution (Efthymiou et al., 2013). Moreover, greenhouse gas (GHG) emissions lower because of a reduction of parking infrastructure, a shift to alternative sustainable modes and a shortening of Vehicle Miles Travelled (Chen and Kockelman, 2016). Furthermore, car sharing vehicles are often equipped with low-polluting engines (Barth and Shaheen, 2002; Catalano et al., 2008; Cervero and Tsai, 2004; Cohen and Shaheen, 2016; Giesel and Nobis, 2016), such as electric power (Cartenì et al., 2016; Mounce and Nelson, 2019). However, the quantification of car sharing effects in greenhouse gas emissions is quite complex (Becker et al., 2018, 2017a), since they are derived from other effects which are difficult to measure, due to uncertainty and approximations needed (Martin and Shaheen, 2011b). Indeed, this evaluation implies an estimation not only of physical impacts, but also of "hidden" impacts, i.e. a proper calculation should include even what would have happened in absence of car sharing (Martin and Shaheen, 2011b). Despite these difficulties, several authors reported a reduction of greenhouse gas emissions after the introduction of car sharing.

Cervero and Tsai (Cervero and Tsai, 2004) analysed variations on gasoline consumption and CO_2 emissions, after the second year of City CarShare in San Francisco, California. In particular, considering VMT, occupancy level of vehicles, engine size, make, year and model of cars and highway conditions, they estimated an average decrease of gasoline consumption and greenhouse gas emissions by 36% and 37%, respectively, for members, whereas non members showed an average increase of gasoline consumption and greenhouse gas emissions by 118% and 118%, respectively. Moreover, comparing results for the first and the fourth year of the service, Cervero et al. (Cervero et al., 2007) calculated a reduction of gasoline consumption of 59% on average for members, and an increase of 46% on average for non members. Martin and Shaheen (Martin and Shaheen, 2011b) used changes in vehicle ownership and travel patterns reported by car sharing members in United States and Canada, before and after joining the service, in order to estimate changes in GHG emissions. In particular, they found that the majority of users increased their annual emissions, but with small magnitudes, therefore the overall effect was an average reduction of 0.58 tons of GHG per year per household (0.84 considering also foregone vehicle purchases). Later, the same authors (Martin and Shaheen, 2016) analysed impacts of car2go in five North American cities, obtaining a decreasing of GHG emission per shared vehicle ranging from 4% (in Calgary) and 18% (in Washington), which was derived considering the reduction of car ownership and VMT. Considering candidate travellers adopting car sharing in United States, Chen and Kockelman (Chen and Kockelman, 2016) quantified the life-cycle reduction in energy and GHG emissions of shared cars compared to private vehicle. In particular, they included in the analysis the effects of changes on car ownership, VMT, shift to alternative modes, parking infrastructure demand and fuel efficiency improvements of the car sharing fleet. In this way they calculated a decreasing of transportation energy use and GHG emissions per member by 51%. Furthermore, they highlighted that the major contribution was given by avoided VMT by private vehicles, while the increase use of public transit and non motorized modes accounted for only 3-5%.

Some authors adopted a simulation approach to quantify car sharing effects on GHG emissions. For instance, Rodier et al. (Rodier and Shaheen, 2003) used the Sacramento regional travel demand model to evaluate potential effects of car sharing. In particular, they found a reduction of CO, NOx and PM emissions of 0.1%, 0.04% and 0.2%, respectively. Similarly, Firnkorn and Müller (Firnkorn and Müller, 2011) used data from a mobility survey administered to car2go members in Ulm, Germany, in order to implement a forecasting model to evaluate CO_2 reduction. Considering changes in car ownership, VMT and modal shift, they obtained a decreasing of CO_2 ranging from 312 to 146 kg per year per user. Moreover, Rabbitt and Ghosh (Rabbitt and Ghosh, 2013) forecasted potential users of car sharing in Dublin, Ireland, predicting a reduction of 86 kt of CO_2 per year (895 kt with particular policies and financial support for car sharing).

Concerning sustainable travel habits encouraged by car sharing, several authors stated that car sharing can promote the diffusion of personal electric vehicle among members (Cartenì et al., 2016). Indeed, Clewlow (Clewlow, 2016) observed that members owned more electric vehicles than non members. In particular, the percentages of hybrid, plug-in hybrid or battery electric cars were about 18% and 10% among users and non users, respectively.

2.5.6. Complex quantification

In the previous paragraphs, some of the main positive reported impacts of car sharing were summarized and analysed. However the quantification of these effects is quite complex (Firnkorn and Shaheen, 2016) for several reasons. First, car sharing is a dynamic system, i.e. the effects of car sharing on travel behaviour change over time (Firnkorn and Shaheen, 2016). For instance, analysing impacts of City CarShare program in San Francisco, Cervero et al. (Cervero, 2003; Cervero et al., 2007, 2006) reported different trends in reduction of VMT and fuel consumption over the five years after the introduction of the service, in 2001. Moreover, car sharing involves mid term and short term decisions. The former is related to decide to join a car sharing system or not; whereas the latter is the choice of which travel mode will be used to carry out a daily activity, conditional on the mid term decision (Kim et al., 2017a). These two perspectives imply uncertainty in modelling car sharing travel demand and consequent impacts (Kim et al., 2017a). In addition, characteristics and travel behaviour of car sharing users vary depending on when they are registered. Indeed, Namazu et al. (Namazu et al., 2018) studied members' attributes and travel habits of residents in Metro Vancouver, Canada. In particular they found that early and late adopters differ respect to household demographics, dwelling attributes and vehicle ownership, indicating that they use car sharing in different ways (Namazu et al., 2018; Namazu and Dowlatabadi, 2018); for instance, only early adopters considered car sharing as a substitution of private cars (Namazu and Dowlatabadi, 2018). Furthermore car sharing effects change according to the operating service model. For instance, comparing members' characteristics and usage patterns of a One-way Free-floating and a One-way Station-Based car sharing services in Basel, Switzerland, Becker et al. (Becker et al., 2017a) reported that the former is used in order to save travel time, complementing public transportation by people living in public transit low served areas, whereas the latter is adopted whenever a car is needed. Moreover, Namazu et al. (Namazu and Dowlatabadi, 2018) analysed survey responses from car sharing users in Vancouver, Canada. The authors showed that both the existing One-way Free-floating and Round-trip systems contributed to reduce car ownership. However users of the former service had a car ownership rates of 1.08 vehicle per household before joining car sharing and 0.98 afterwards. Whereas, Round-trip users decreased their rates from 0.68 to 0.36. Because of these aspects, different authors reported different impacts of car sharing.

2.6. Data sources and methods

2.6.1. Data sources

Revealed-preferences dataset

The most used type of dataset was Revealed-preferences data, collected after the introduction of car sharing, in order to understand members' characteristics and travel behaviours. Therefore many authors considered only users who joined the service (Alonso-Almeida, 2019; Clark et al., 2015; Coll et al., 2014; Firnkorn, 2012; Kim et al., 2015; Kopp et al., 2013). Information were gathered through ad hoc surveys (Alonso-Almeida, 2019; Becker et al., 2017b; Kopp et al., 2015), data from operators (Coll et al., 2014; Kopp et al., 2013), census datasets (Celsor and Millard-Ball, 2007) or national travel surveys (Becker et al., 2017c; Clewlow, 2016; Dias et al., 2017; Juschten et al., 2017).

In order to estimate impacts of car sharing, several authors adopted Revealed-preferences surveys administered before and after the introduction of the service (Becker et al., 2017a; Cervero, 2003; Cervero et al., 2007; Cervero and Tsai, 2004; Martin et al., 2010). Setting the proper point in time when the effects are estimated is quite challenging (Firnkorn, 2012), since travel behaviours of early adopters are different if compared to late adopters (Cervero et al., 2006). Indeed Cervero, Cervero and Tsai, and Cervero et al. (Cervero, 2003; Cervero et al., 2007; Cervero and Tsai, 2004) reported different impacts repeating the same survey one year, two years and four years after City CarShare introduction in San Francisco. The majority of before-after datasets was collected through ad hoc surveys, such as travel diaries (Becker et al., 2018; Cervero et al., 2006; Cooper et al., 2000; Martin and Shaheen, 2016, 2011b; Shaheen et al., 2018). Moreover, since the main aim was to evaluate car sharing impacts, most of the authors considered only members (Becker et al., 2018; Dill et al., 2019; Lane, 2005; Le Vine and Polak, 2019; Lempert et al., 2019; Shaheen et al., 2018), whereas others included both members and non members in their analysis (Celsor and Millard-Ball, 2007; Dias et al., 2017; Kopp et al., 2015; Namazu et al., 2018; Sioui et al., 2012).

In these studies many factors that pre-dispose a person to use car sharing might shape her travel decisions, leading to misestimating impacts of this service. In this case, self-selection bias might occur, i.e. impacts of car sharing might be due to the differences between members and non members, rather than to car sharing membership. In order to avoid biased results, few authors created a control group of non users (Firnkorn, 2012), thus isolating the actual effects of joining car sharing from external effects (Becker et al., 2018). Nevertheless, the choice of the approach to select the control group is difficult, since even the adopted arbitrary selection procedure might affect users' responses and related estimated results (Firnkorn, 2012). Cervero and Tsai (Cervero and Tsai, 2004) and Cervero et al. (Cervero et al., 2007) were the first authors trying to address this issue, by comparing results from a panel of members and non members, however the control group was affected by self-selection bias (Becker et al., 2018). Clewlow (Clewlow, 2016) created a control group consisting of persons living in a census tract with at least one shared vehicle. Mishra et al. (Mishra et al., 2015) developed a non parametric matched sampling approach to generate a control group which was statistically balanced on socio-economic variables, residential locations and travel behaviour. In a later work the same authors (Mishra et al., 2017) adopted a score based matching procedure to identify a control group whose distribution of covariates matched the group of car sharing members. In the same paper, the authors addressed also simultaneity bias, which occurs when an explanatory variable is simultaneously a function of the dependent variable to be explained, i.e. the same variable is both a cause and an effect (Mokhtarian and Cao, 2008). This bias might affect the estimation of changes in vehicle holdings, since the dynamic process of car ownership might influence membership decision, which in turn might influence holding in later period (Mishra et al., 2017).

Stated-preferences dataset

In order to avoid these drawbacks, an alternative is to adopt a Stated-preferences approach for both members and non members. This method was used also to forecast the impacts of car sharing before its introduction or when Revealed-preferences data were few (Heilig et al., 2017). Stated-preferences survey has some advantages. For example, it allows the researcher to have more control of choice situations (Ortuzar and Willumsen, 2011) and the recruitment of participants is easier, since observing the real behaviour under analysis is not necessary (Heilig et al., 2017). However, this technique has also some disadvantages. Respondents often tend to cast their actual behaviour in a better light, leading to self-selection bias (Ortuzar and Willumsen, 2011). Moreover answering fatigue grows with the complexity of experiments (Heilig et al., 2017). In addition, respondents might be not familiar with proposed alternatives, leading to unreliable answers (Diana, 2010). Some authors used Stated-preferences experiments at trip level (Carroll et al., 2017; Catalano et al., 2008; de Luca and Di Pace, 2015; Kim et al., 2017a; Rotaris et al., 2019; Winter et al., 2017; Yoon et al., 2017), others at individual level, testing the willingness to join the service (Acheampong and Siiba, 2019; Burghard and Dütschke, 2019; Efthymiou et al., 2013; Efthymiou and Antoniou, 2016; Rotaris and Danielis, 2018; Wang et al., 2017) or to adopt particular vehicles, such as electric cars (Kim et al., 2015; Zoepf and Keith, 2016).

Target population and sample

Most of the above mentioned studies did not use a representative sample of the population under analysis, therefore results are not generalizable. With the notable exceptions of Becker et al. (Becker et al., 2017c, 2017a, 2017b), Clewlow (Clewlow, 2016), Clewlow and Mishra (Clewlow and Mishra, 2017) and Rodier and Shaheen (Rodier and Shaheen, 2003), many authors considered a non stratified random sample of the population (Kim et al., 2017c, 2017b; Le Vine et al., 2014a; Lempert et al., 2019; Namazu et al., 2018; Perboli et al., 2017; Rotaris and Danielis, 2018; Shaheen et al., 2018; Sioui et al., 2012; Wang et al., 2017, 2012), a particular segment of travellers (Acheampong and Siiba, 2019; Efthymiou et al., 2013), such as students (Guirao et al., 2018; Rotaris et al., 2019; Zheng et al., 2009) or employees (Clark et al., 2015; de Luca and Di Pace, 2015; Zhou, 2012). On the other hand, other authors adjusted the representativeness of the sample adopting weighting schemes. For instance, Zhou and Kockelmann (Zhou and Kockelman, 2011) stratified the analysed sample according to traffic analysis zones, obtaining a sample biased in the level of education, age and income, which was corrected using weights from census data on the study area. Nobis (Nobis, 2006) randomly selected interviewees and, after collecting survey responses, they checked the representativeness of the sample using a national travel survey. Similarly, Stasko et al. (Stasko et al., 2013) compared the collected sample of car sharing members with the whole population of Ithaca Carshare users, obtaining good representativeness. Other authors focused Stated-preferences experiments on a hypothetical trip with attributes which were not really experienced by interviewees (de Luca and Di Pace, 2015; Efthymiou et al., 2013; Efthymiou and Antoniou, 2016; Winter et al., 2017), leading to unreliable answers.

Few authors focused on other targets with different aims. Shaheen et al. (Shaheen et al., 2015) interviewed 31 car sharing organizations in the Americas, in order to estimate their perspectives and the future of the service. Terrien et al. (Terrien et al., 2016) administered a survey to car sharing operators and government staff in Europe and United States, in order to understand the dynamic developing of the systems. Münzel et al. (Münzel et al., 2018) analysed all car sharing business models in Germany. In 2006, 2008 and 2010 Shaheen et al. (Shaheen and Cohen, 2013) interviewed 80 car sharing experts of several nations in the world, in order to evaluate car sharing growth and future development.

Transaction data and GPS tracks

Other data sources to study travel behaviours of members include transaction data and GPS tracks of shared vehicles (Wielinski et al., 2018). The former are related to booking data (de Lorimier and El-Geneidy, 2012; Seign et al., 2015; Wielinski et al., 2018) with (Habib et al., 2012; Hu et al., 2018b, 2018a; Jian et al., 2017; Morency et al., 2012; Schmöller et al., 2015) or without users' characteristics (Lee et al., 2016; Morency et al., 2007; Sprei et al., 2018). The latter are data streams of car sharing trips, containing subsequent positions of vehicle movements (Dill et al., 2019; Kopp et al., 2015; Wielinski et al., 2018). For instance, Becker et al. (Becker et al., 2017b) used combined transaction data and vehicle movements, with travel diaries and geo-spatial data in order to understand the characteristics of travel demand of a Free-floating car sharing service in Basel. Dill et al. (Dill et al., 2019) used GPS data of cars and in-depth surveys to estimate impacts of Peer-to-peer car sharing in Portland.

2.6.2. Methods

In order to evaluate changes in travel behaviour of travellers and impacts after the introduction of car sharing services, different methodologies were adopted, depending on the available data source and the aim of the analysis. Adopted approaches can be grouped in: statistical methods, both descriptive and inferential, random-utility based models, data mining techniques, simulation and optimization approaches.

Statistical approaches

Descriptive statistics is the most adopted techniques and it was often used to perform preliminary analysis of the sample (Becker et al., 2017a; Cervero, 2003; Costain et al., 2012b, 2012a; Dill et al., 2019; Guirao et al., 2018; Lane, 2005; Shaheen et al., 2015). On the other hand, statistical inference allows drawing conclusions about unknown properties of the population, based on a random sample of that population (Alonso-Almeida, 2019; Burghard and Dütschke, 2019; Celsor and Millard-Ball, 2007; Clark et al., 2015; Seign et al., 2015). Several authors adopted these techniques to understand the differences between two samples of the population. For instance Cooper et al. (Cooper et al., 2000) used descriptive statistics to show differences between socio-economic characteristics and travel behaviour of citizens of Portland and car sharing members of the same city. Martin et al. (Martin and Shaheen, 2016) analysed data of car2go members to highlight the effect of joining car sharing. Becker et al. (Becker et al., 2018) adopted a difference-in-difference approach to estimate changes in car ownership, comparing a sample of car sharing members and a control group. Shaheen et al. (Shaheen et al., 2006) described the market dynamics of car sharing services in North America.

Several authors adopted linear (Lempert et al., 2019) and logistics regressions (de Lorimier and El-Geneidy, 2012; Hu et al., 2018b). Nobis et al. (Nobis, 2006) used linear regression to understand variables related to car sharing acceptance, and logistic regression to model monomodal and multimodal behaviours. Similarly, Zheng et al. (Zheng et al., 2009) developed logistic regression models to evaluate willingness to participate in two car sharing plans. Ko et al. (Ko et al., 2019) and Le Vine et al. (Le Vine and Polak, 2019) used logistic regressions to analyse impacts on car ownership.

Other authors adopted factor analysis (Nobis, 2006). For instance, Efthymiou et al. (Efthymiou et al., 2013) used this technique to synthetize variables affecting the decision to own a car in Greece. Kim et al. (Kim et al., 2015) applied factor analysis to identify factors influencing the satisfaction of the current electric car sharing program, in Seoul. Similarly, in the same city, Ko et al. (Ko et al., 2019) adopted this method to create variables describing the satisfaction level of car sharing, which were introduced in car disposal and purchase models.

Random-Utility based Models

In order to understand and simulate travel behaviour of users, starting from the work of McFadden (McFadden, 1974), models based on Random Utility Maximization theory has been extensively adopted (Tang et al., 2015; Yamamoto et al., 2007), in particular multinomial logit (Hagenauer and Helbich, 2017; Moons et al., 2007; Sekhar et al., 2016; Xie et al., 2007) (MNL). However, these models are based on several statistical and mathematical assumptions on data used to calibrate them (Chen et al., 2018; Yamamoto et al., 2007); if these assumptions are violated, errors in the estimation of parameters might occur, leading to biased prediction results (Chen et al., 2018; Hagenauer and Helbich, 2017; Lindner et al., 2017; Xie et al., 2007). In particular, MNL requires independence of irrelevant alternatives (IIAs) (Chen et al., 2018; Hagenauer and Helbich, 2017; Lindner et al., 2017; Tang et al., 2015; Xie et al., 2007), i.e. the effect of attributes are compensatory (Xie et al., 2007; Yamamoto et al., 2007). Several models were developed in order to overcome these limitations, such as probit models (Train, 2003). Furthermore, in order to introduce correlation effects among alternatives, nested logit, cross-nested logit, ordered generalized extreme values and mixed logit models were implemented (Zhu et al., 2018).

In case results of the prediction were binary outcomes, several authors adopted binomial logit or probit models. For example, Cervero (Cervero, 2003), Cervero and Tsai (Cervero and Tsai, 2004) and Cervero et al. (Cervero et al., 2007) used binomial logits to model car ownership and car sharing usage. Costain et al. (Costain et al., 2012b, 2012a) adopted this type of model to understand the decision of car sharing members to buy carbon offsetting and collision deductible in Toronto. Habib et al. (Habib et al., 2012) and Morency et al. (Morency et al., 2012) used a binary probit to estimate the probability to be an active member in any month in Montreal. Becker et al. (Becker et al., 2017a) and Juschten et al. (Juschten et al., 2017) developed a binomial logit model to predict car sharing membership in Basel and in Switzerland, respectively. With the same aim, Becker et al. (Becker et al., 2017c) introduced latent variables in a multivariate probit model, which simultaneously models multiple correlated binary outcomes. Dill et al. (Dill et al., 2019) estimated a binomial logit to predict whether car owners of Peer-to-peer car sharing reduced the use of their vehicle.

On the other hand, if the outcome was an ordered variable, ordinal logit and probit models were used. For instance, Efthymiou et al. (Efthymiou et al., 2013) adopted an ordered logit model to understand the satisfaction of current travel patterns of young Greek travellers. Kim et al. (Kim et al., 2015) analysed willingness to use car sharing electric vehicles and to dispose a private car, through an ordered probit. Efthymiou and Antoniou (Efthymiou and Antoniou, 2016) implemented an ordered logit to model the willingness of young Greeks to join car sharing, introducing latent variables. Becker et al. (Becker et al., 2017a) developed an ordered probit to estimate the frequency of use of car sharing in Basel. In order to evaluate car sharing frequency of use in Washington State, Dias et al. (Dias et al., 2017) adopted a bivariate ordered probit model. Recently, Ko et al. (Ko et al., 2019) implemented an ordered probit to study car ownership changes after participating in car sharing, in Seoul.

When the variable to predict was categorical with multiple levels, Multinomial Logit models were developed. In San Francisco, Cervero et al. (Cervero et al., 2006) analysed car sharing adoption including this mode in a MNL. Catalano et al. (Catalano et al., 2008) adopted MNL to forecast mode choice in the city of Palermo, Italy, adopting four alternatives: private car, public transport, car sharing and car pooling. Costain et al. (Costain et al., 2012b, 2012a) developed a MNL to analyse the choice of vehicle type for car sharing members in Toronto. Carrol et al. (Carroll et al., 2017) used a MNL to model mode choice of citizens of Dublin, considering private car, car sharing and car pooling. Other authors adopted a mixed logit model, in which some coefficients of variables in the utility formula are modelled as random variables. Rotaris et al. (Rotaris et al., 2019) used a mixed logit to understand how the adoption of car sharing would change among college students in Milan and Rome, Italy, varying the attributes of the current service. Zoepf et al. (Zoepf and Keith, 2016) compared the performances of MNL and mixed logit in quantifying how members trade off service attributes in car sharing reservation decision. Some authors adopted other types of logit models, such as nested logit. Winter et al. (Winter et al., 2017) used a nested logit to model mode choice in the Netherlands, considering also shared autonomous vehicles. De Luca and Di Pace (de Luca and Di Pace, 2015) used MNL, cross-nested logit and mixed logit to forecast the effects of an inter-urban car sharing service near Salerno, Italy.

Data mining

Overcoming previously explained drawbacks (Lindner et al., 2017), data mining techniques do not require any statistical and mathematical assumption on data structure (Chang and Chen, 2005; Tang et al., 2015; Thill and Wheeler, 2007; Zhang et al., 2017). Furthermore, they have a more flexible structure (Tang et al., 2015; Wang and Ross, 2018; Xie et al., 2007; Yamamoto et al., 2007; Zenina et al., 2018), rather than traditional logit models, extracting significant patterns from the dataset and leading to a deeper understanding of relationship among explanatory variables (Chang and Chen, 2005; Chen et al., 2018; Hagenauer and Helbich, 2017; Lindner et al., 2017; Pitombo et al., 2011; Tang et al., 2015; Xie et al., 2007; Yamamoto et al., 2007; Zenina et al., 2018). Moreover they can be easily applied to large databases (Zhu et al., 2018), even with high unbalanced data (Wang and Ross, 2018).

On the other hand, results that are quite useful for planning and forecasting purposes and that are commonly derived through an econometric approach, such as the Value Of Time and demand elasticities, cannot be obtained from such techniques, which are very sensitive to training data (Zhu et al., 2018). Furthermore they often lack of interpretability, indeed they tend to focus more on predictive accuracy rather than on counterfactual analysis (Waddell and Besharati-Zadeh, 2019). Even if, recently, some authors were able to extract interpretable economic information, such as elasticities, from a data mining approach (Wang and Zhao, 2018). In transportation analysis, data mining techniques were mostly used to reproduce existing scenarios (Pitombo et al., 2011; Wang and Kim, 2019), modelling users' choice based on current conditions and options (Yamamoto et al., 2007; Zhang et al., 2017). Although traditional mode choice models are based on random utility maximization theory, data mining techniques were used to predict future travel behaviour of users, and in particular, mode choices of travellers (Pitombo et al., 2015). Following this approach, mode choice can be defined as a pattern recognition task in which multiple behavioural attributes described by explanatory variables determine the prediction of the choice among different alternatives (Pitombo et al., 2015; Xie et al., 2007). Therefore data mining approach can be adopted for modal analysis and prediction.

For example, Morency et al. (Morency et al., 2007) used cluster analysis to identify different type of car sharing users in Montreal. Schmöller et al. (Schmöller et al., 2015) adopted the same technique to define group of days with similar spatial booking patterns in Munich and Berlin, Germany. Lee et al. (Lee et al., 2016) applied Association Rules to show relationships among variables related to a car sharing service in Cagliari, Italy (such as rate plan and vehicle type). Wang et al. (Wang et al., 2017) implemented a hierarchical tree based regression to understand factors affecting the choice to join a car sharing electric service in China. With a similar aim, Hu et al. (Hu et al., 2018b) applied a Random Forest in Shanghai, China.

Simulation

Some of the previously explained approaches were introduced as mode choice models in travel simulators, estimating travel demand and its effect in traffic networks. For instance, Rodier and Shaheen (Rodier and Shaheen, 2003) introduced the car sharing option in a four-step model in the Sacramento region, California, in order to estimate travel demand, emissions and economic benefits for travellers. Li et al. (Li et al., 2018) developed an Activity-Based model, including a One-way Free-floating service, to model the dynamic choice of car sharing. Ciari et al. (Ciari et al., 2014) used an Agent-Based model to evaluate the use of One-way Free-floating and the existing one-way Station-based, in Berlin. Fagnant and Kockelman (Fagnant and Kockelman, 2014) adopted an Agent-Based simulation technique to study the impacts of shared autonomous vehicles in car ownership and traffic pollution. Ciari et al. (Ciari et al., 2015) implemented an Activity-based Multi-Agent model to estimate the effects in travel demand of different pricing strategies of a car sharing service in Zurich. Heilig et al. (Heilig et al., 2017) developed a combined destination and mode choice model, which included car sharing, in order to introduce it in an Agent-Based model in Stuttgart, Germany. Martinez et al. (Martínez et al., 2017) used the same type of model to simulate the daily operation of a car sharing service in Lisbon.

Optimization approaches

Some authors adopted optimization techniques to solve problems related to car sharing services and operations. For instance Correira and Antunes (Correia and Antunes, 2012) developed an optimization model to depot location with different trip selection schemes of an One-way car sharing operator in Lisbon, maximizing its profits. Later, Correira et al. (Correia et al., 2014) improved the previous work considering the user's flexibility in choosing a car sharing station. Jorge et al. (Jorge et al., 2015a) developed an algorithm to optimize a car sharing system which can work both as Round-trip and One-way, in case of a specific generator of high travel demand; moreover they applied their model to the airport of Boston. Jorge et al. (Jorge et al., 2015b) adopted an optimization approach to design the best trip pricing for a One-way car sharing service in Lisbon, in order to maximize its profits. Recently, considering time-dependent and uncertain travel demand, Hua et al. (Hua et al., 2019) proposed a model to optimize both long-term and real-time operations of an electric vehicle car sharing operator in New York. The formers are related to infrastructure planning, such as the location of charging stations and fleet distribution, whereas the latter consider fleet operations, such as relocation of cars and charging decisions.

2.7. Conclusions and research gaps

As described before, car sharing has different social, environmental and land use impacts. Most of them are positive, such as a reduction of car ownership, due to users who decide to dispose of an owned vehicle or not to buy an extra car after joining the service. This contributes to decrease the parking space occupied by private vehicles; in this way, cities with limited public areas can gain further space for different land uses. The decreasing private car usage induces travellers to adopt alternative and more sustainable transport modes, such as public transport, bike and walking. Furthermore, the introduction of car sharing is found to reduce vehicle miles travelled, since users lowered the number of their private cars; in addition, they became more conscious of driving cost and, consequently, they used vehicles more appropriately, shortening travel distances. Moreover, car sharing contributes to reduce carbon fossil emissions, as a consequence of these aspects and since fleets are often equipped with efficient low-emission or electric engines. However, the quantification of these impacts is often difficult and uncertain, due to the complexity of this evaluation. Therefore estimating and analysing travel demand of this mode is important to evaluate these impacts, thus providing sound basis to policy makers and local authorities, who have to decide whether to address public resources to promote car sharing.

Furthermore, car sharing can significantly alter the modal share of travellers, since it can substitute or complement existing travel means, with relationships that are still not clear and often site-specific. In particular, car sharing can complement public transport solving the “first and last miles” problem, increasing its spatial and temporal accessibility, since car sharing can be used in areas with low public transport penetration or in time periods when it is less frequent. However car sharing can also substitute transit for systematic trips. This controversial relationship can change according to car sharing operational model, due to different types of trips which can be addressed by each service model. The same ambiguity is reported for bike, walking and taxi. Moreover competitiveness can arise even among car sharing operators with different business models within the same city. The analysis of complementarity and substitution patterns can help transportation planners and policy makers in providing travellers with a range of mobility options which can accommodate all their mobility needs. In addition, previously described benefits can be effective only if car sharing is able to attract private car drivers and, therefore, if it does not substitute other existing sustainable modes (such as public transport, bike and walking).

According to this last consideration, few authors developed specific analysis for each transport modes that car sharing can substitute. In the present work of thesis, the effect of car sharing on existing travel modes is modelled by separately considering the shift from private car, public transport, bike and walking. In this way, it is possible to identify factors affecting the choice to switch to car sharing and the relationships of complementarity and/or substitution between car sharing and each travel modes. Therefore, through the proposed approach, the use of car sharing can be promoted or avoided, by varying mode-specific factors.

Furthermore modelling results of the switch from private car towards car sharing are used to quantify the reduction of public space. Unlike previous works, the decreasing of parking space is not linked to car ownership changes. On the contrary, through the developed method, the new parking configuration is related to the different modal share of travellers deciding to adopt car sharing.

In order to reach these aims, different models and methods are adopted: logit models based on Random Utility Theory, data mining techniques and a new visual approach. Each technique can complement each other providing different information, which are useful to create the global framework to model travel demand, to estimate impacts after the introduction of car sharing and to define the best ambit of use of each travel means.

Data used to calibrate and apply proposed approaches are obtained from a travel survey, carried out in the Municipality of Turin, where three One-way car sharing services are operating. Unlike the majority of previous works, this survey was administered to a representative sample of the population living in the study area. Therefore results are reliable and can be generalized to the whole universe[1] of the population living in the study area. It is worth noting that obtained results are site-specific and, for this reason, they cannot be transferred to other cities or countries. Furthermore, the survey contains also a section with Stated-preferences experiments. Differently from previous works where these choices tasks are based on a hypothetical trip, in this case, travellers are asked about using different transport modes in the future, referring to a trip that was performed before the interview. Therefore respondents focused on a real trip, rather than an abstract choice. Moreover, attributes of the opt-out alternative are those directly obtained from the reported trip, and attributes of the alternative modes are derived from the real transportation network, public transport agencies and information about current car sharing services. These aspects increase the realism and reliability of respondents' answers, thus providing sound basis for the results of applied modelling approaches.

[1]Here and in the following, the universe is considered, from a statistical point of view, as the population of interest from which a sample is selected in order to represent it with certain attributes (Hensher et al., 2005; Ortuzar and Willumsen, 2011).

Chapter 3

Study area description

3.1. Characteristics of the study area

The study area is located in the North-Western part of Italy. It consists of the metropolitan area of Turin, which is made by the municipality of Turin and the municipalities surrounding the city. In the former, there are about 800’000 inhabitants on about 130 square kilometres, whereas in the latter there are about 544’000 inhabitants on about 708 square kilometres. The population density is around 7’014 inhabitants for square kilometre in Turin and around 909 inhabitants for square kilometre outside the city (Agenzia per la Mobilità Metropolitana e Regionale, 2015).

In the whole area, about 2’962’000 trips were estimated to be performed in a generic non-working day in 2015 (Agenzia per la Mobilità Metropolitana e Regionale, 2015). Moreover, 48.3% of them were carried out using a private travel means, 18% on public transport and 33.7% on active modes (Agenzia per la Mobilità Metropolitana e Regionale, 2015). In the province of Turin, which includes all the study area, the motorization rate is about 664 private cars per 1000 inhabitants, in 2017, which is one of the highest in Italy, and it grew by 5.5% from 2015 to 2017 (Regione Piemonte, 2017).

Furthermore, most of the inhabitants in the Turin metropolitan area are satisfied with the different transport services; in particular, in 2013, about 83% of the population was satisfied with the public transport services, 88% with their private car and 92% with bike (Agenzia per la Mobilità Metropolitana e Regionale, 2015). As regards public transit, the most attractive mode is the metro, followed by train, suburban and urban buses (Agenzia per la Mobilità Metropolitana e Regionale, 2015). About 50% of public transport users adopted this mode since a car was not available, whereas 16% since they could avoid the problem of parking, and only 7% since it is cheaper than car. Considering car drivers, 33% of them used personal vehicles since the travel time is shorter, about 21% since the public transport system was not available or not appropriate, and around 10% since private car provides more comfort and privacy. On the other hand, 30% of bikers choose this mode since it allows great flexibility, 16% since they could also keep fit, and about 22% since they could save money and time (Agenzia per la Mobilità Metropolitana e Regionale, 2015).

In general, the diffusion of private car and the global satisfaction with public transport and other active modes in the metropolitan area of Turin, make this study area a good testbed for the analysis of the introduction of car sharing service, since this mode was introduced where the use of existing travel means was consolidated.

The study area was divided into 54 Traffic Analysis Zones, adopting the same zoning used by the local mobility agency (Agenzia della Mobilità Piemontese). According to this authority, the municipality of Turin is divided into 23 zones, each of them corresponding to a neighbourhood. Figure 2 represents these zones and Table 1 reports the name of the code of each zone. Moreover, each of the 31 municipalities that surround Turin corresponds to a specific zone, as depicted in Figure 3 and reported in Table 2.

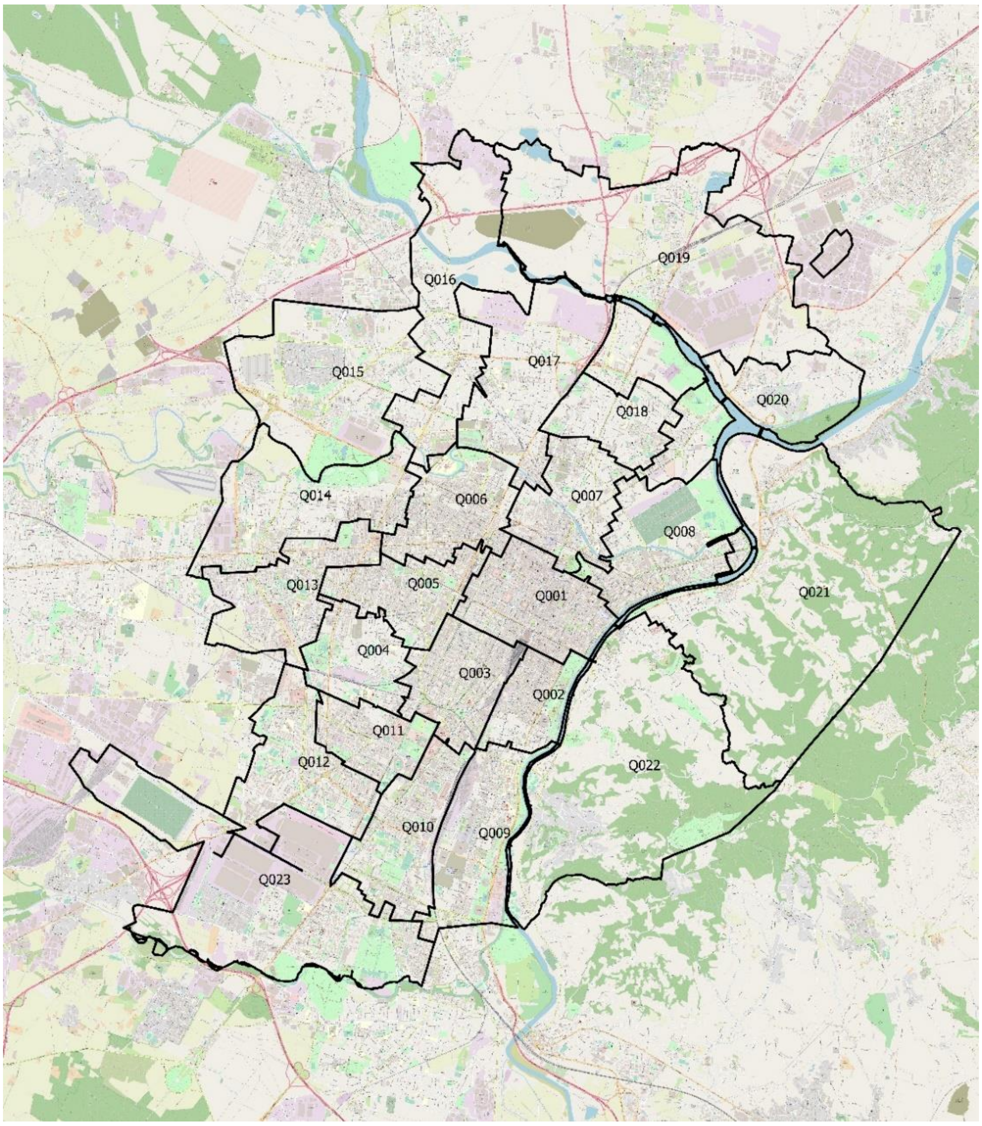

Figure 2. Traffic Analysis Zones within the Turin Municipality (codes in the table below)

Table 2. Codes for the Traffic Analysis Zones within the Turin Municipality

Code	TAZ name	Code	TAZ name	Code	TAZ name
Q001	Centro	Q009	Nizza Millefonti	Q017	Borgo Vittoria
Q002	San Salvario	Q010	Mercati generali	Q018	Barriera di Milano
Q003	Crocetta	Q011	Santa Rita	Q019	Rebaudengo Falchera
Q004	San Paolo	Q012	Mirafiori Nord	Q020	Regio Parco Barca
Q005	Cenisia	Q013	Pozzo Strada	Q021	Madonna del Pilone
Q006	San Donato	Q014	Parella	Q022	Cavoretto Borgo Po
Q007	Aurora	Q015	Le Vallette	Q023	Mirafiori Sud
Q008	Vanchiglia	Q016	Madonna di Campagna		

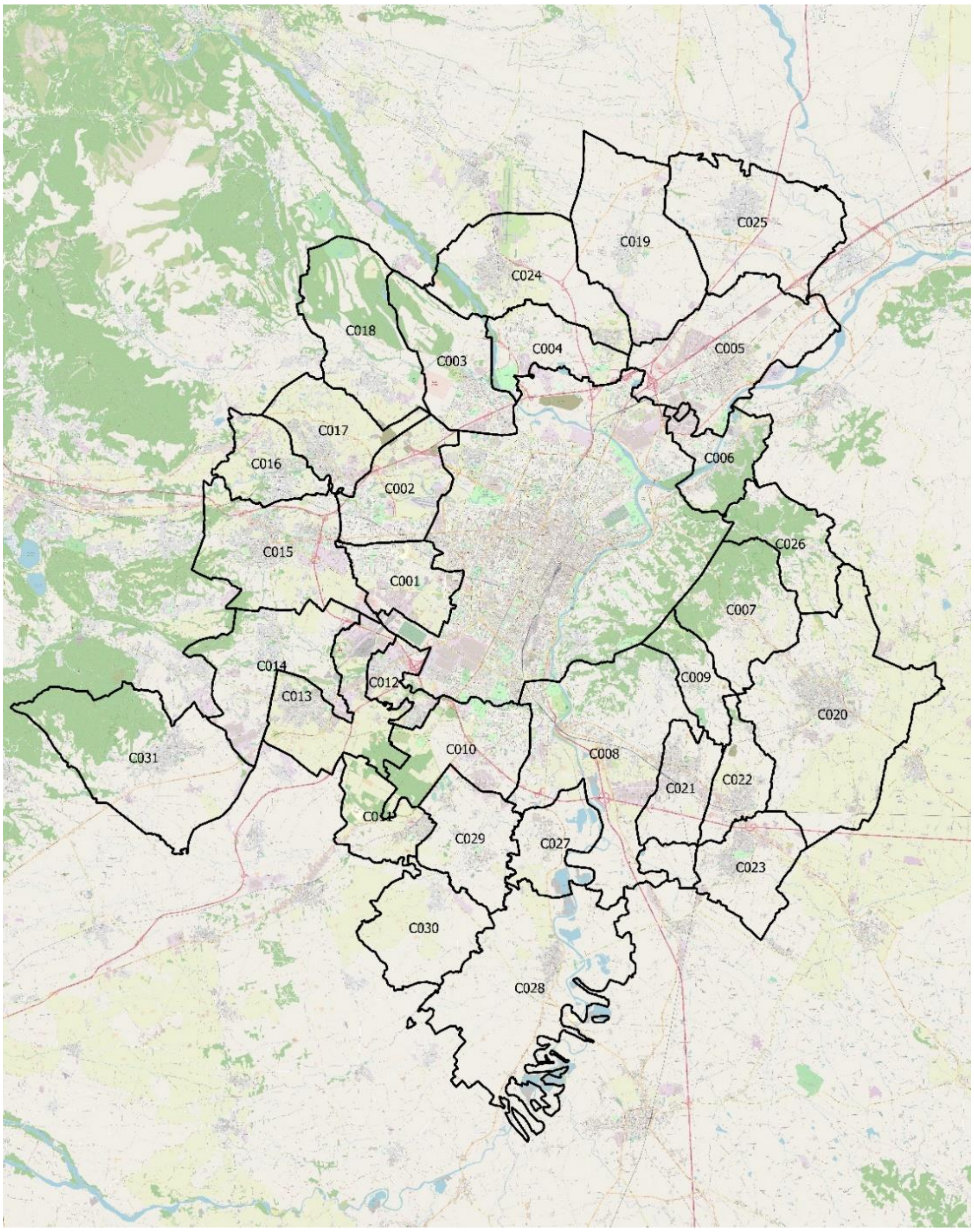

Figure 3. Traffic Analysis Zones corresponding to municipalities surrounding the Municipality of Turin (codes in the table below)

Table 3. Codes for the Traffic Analysis Zones outside the Turin Municipality

Code	TAZ name	Code	TAZ name	Code	TAZ name
C001	Grugliasco	C012	Beinasco	C023	Santena
C002	Collegno	C013	Orbassano	C024	Caselle Torinese
C003	Venaria	C014	Rivalta di Torino	C025	Volpiano
C004	Borgaro Torinese	C015	Rivoli	C026	Baldissero Torinese
C005	Settimo Torinese	C016	Alpignano	C027	La Loggia
C006	San Mauro Torinese	C017	Pianezza	C028	Carignano
C007	Pino Torinese	C018	Druento	C029	Vinovo
C008	Moncalieri	C019	LeinI	C030	Piobesi Torinese
C009	Pecetto Torinese	C020	Chieri	C031	Piossasco
C010	Nichelino	C021	Trofarello		
C011	Candiolo	C022	Cambiano		

3.2. Car sharing services in Turin

In Italy, car sharing was promoted and regulated by a national rule in 1998 (Ministero dell'Ambiente, 1998), through which the Italian Government provided financial support to municipalities to introduce car sharing services in their cities. This regulation was included in a wide framework of actions to reduce air pollution in urban areas. Starting from this rule, in 2001, some Italian municipalities became partners, creating the program *Iniziativa Carsharing* (ICS), in order to implement car sharing services sharing common and standardized guidelines.

In Turin, car sharing was introduced in 2002 with ICS. In 2015 two One-way Free-floating operators (Car2go and Enjoy) began their services in the city, with about 930 gasoline vehicles in July 2016, which represented 16% of the total number of shared cars in Italy. In 2015, Turin became the third Italian city for car sharing penetration (after Florence and Milan), since the number of shared vehicles was 10.44 per 10'000 inhabitants, 7.15 squared kilometre and 1.60 per 1000 private cars (Ciuffini et al., 2017). In the same year, the number of car sharing members was 51'522, with about 20% of frequent users, the number of rents was 484'770, with an average length of 5 kilometres per trip (Ciuffini et al., 2017). In 2016 a One-way Station-based car sharing operator (Bluetorino) with about 120 electric cars was introduced. At the end of 2016, 6% of residents were car sharing members, with 3.1 rents per car each day, and an average length of 5.3 kilometres per trip (Ciuffini et al., 2018). In December 2017, in Turin, there was about 15% of the total number of shared vehicles in Italy, with about 902 cars (Ciuffini et al., 2019). However, from September 2016 to February 2017, although the overall fleet size in the city decreased by 8%, the number of trips grew by 54% (Urbi, 2017). In 2018, even if the total number of shared vehicles remained constant (908 cars, 721 gasoline vehicles and 187 electric vehicles), the average number of rents per shared car grew up to 6.2 per day (Ciuffini et al., 2019). Nowadays, the two One-way Free-floating operators have about 720 gasoline vehicles with about 151'000 members, whereas the One-way Station-based service has 190 electric cars with 54 charging stations and about 3'000 members (Ciuffini et al., 2019). The growing demand for the service, along with the contextual presence of operators with different schemes, makes the city of Turin an interesting study field for car sharing systems.

Chapter 4

DEMONSTRATE survey results

The following paragraphs present some analyses on the dataset originating from the DEMONSTRATE survey that is documented in is exploited in the present research. The survey was designed and partly implemented before the start of the research activity described in this Ph.D. thesis, within the framework of the DEMONSTRATE project ("La Ricerca dei Talenti" competitive call funded by Fondazione CRT, principal investigator prof. Marco Diana). However, since these surveying activities have not yet been documented in the open literature, related information are reported in Appendix A, to which interested readers are referred. In order to make sure that the reader can easily follow the analyses reported in this chapter, a short description of the field activities was summarized hereinafter.

The survey was administered to a representative sample of the population living in the study area (the municipality of Turin and the municipalities surrounding the city). In order to reach this target, a stratified random sample technique was adopted, where strata were created according to gender, age, occupational status and traffic analysis zone where the individual lives. Only persons 18 aged and more were considered, since, in Italy, people under 18 years cannot have a driving license.

The survey contains a brief introduction with preliminary screening questions (gender, age, occupation and zone) to understand which stratum the interviewee belongs to. Then, travel diary and related activity patterns spanning over the 24 hours before the interview were collected. Location were entered through Google Maps APIs (Google LLC, 2019a) to better estimate travel times and covered distances, duration and type of activities, and transport modes used to reach each place. After that, a trip chain composed by trips shorter that 50 km and/or carried out inside the study area among those listed in the travel diary was randomly selected (named macro-trip in the following). The aim of this procedure was to increase the degree of realism for the respondent related to urban transport modes under analysis. Detailed questions were posed about this macro-trip, concerning, for example, travel times with all means, walk and wait times, travel contingencies, info on vehicles, on-trip activities. Moreover users were asked about additional information on each mode that was used (e.g. cost, duration, presence of parking, number of persons, use of different modes in the past to complete the same trip), and attitudinal questions (e.g. intention to use different modes in the future to complete the same trip, possible accidents, satisfaction levels through a valence and activation scale (Ettema et al., 2011, 2010)).

Then, in order to investigate mode switching attitudes for the chained trip, stated preferences experiments were carried out. These were based on an improved version of the survey presented in Diana (Diana, 2010, 2008). The respondent had to declare her preference between two transport modes, assuming that she had to complete the same trip chain she reported in the survey again in the future. The first mode was the already used one (in case more than one was used, the mode used for most of the time to complete all trips composing the trip chain was automatically selected). The latter was one alternative switching mode among the following six: car as driver, car sharing, public transport, bike, bike sharing and a kind of shared taxi in which users share the ride with other passengers booking their trip in. Therefore, each respondent had to face with six experiments, one for each of the six alternative modes. In each experiment she had to choose one mode between the mean currently adopted and the alternative one. Please note that whenever the current mode was equal to one of the six alternative switching modes, then the corresponding stated preferences experiment proposed the same mode for the two alternatives, which had however different attributes according to the below explanations. For the experiment implementation an orthogonal fractional design (Ortuzar and Willumsen, 2011) was developed, with 3 levels for each of the 4 trip attributes, generating 18 questions divided into 3 blocks.

Answers were elicited on a 5-points scale ranging from “I am not at all inclined to use the switching mode” to “I am strongly inclined to use the switching mode”, going through a neutral point. In order to increase the realism and to obtain reliable answers, in each experiment, beyond the attributes of both the current and of the switching mode, a reminder displayed information about the selected trip chain. In particular time and type of activities carried out in the origin and destination of the trip chain, and the main mode indicated in the Revealed Preferences part of the survey, were shown. The following four attributes were considered:

- in-vehicle time;
- walking time to reach the public transit stop and waiting time at the stop (for public transport modes);
- walking time to reach the parked vehicle (for car, car sharing and bike sharing);
- costs: public transit ticket or subscription (for public transport modes), tolls, fuel and parking fares (for car), other fares (for car sharing, carpooling and bike sharing).

Attributes of the current mode were calculated by directly considering the corresponding answers on the relevant items. Attributes of each of the six switching modes were rather estimated by processing information on the trip chain (e.g. geographical locations, departure/arrival times) through Google Maps APIs, additionally integrating information related to public transit operations, car sharing and bike sharing services (namely, fares and subscription costs), along with average cost of fuels. In this way, Stated-preferences attributes are very close to the attributes of the corresponding trip carried out with the alternative mode. Therefore, the experiment is based on a real trip with realistic characteristics of the switching mode. In particular, respondents can focus on an actually performed trip. Since users’ answers to Stated-references experiments are based on these personal experiences, they have sound basis and, therefore, they are considered as reliable, reflecting real switching intentions. Lastly, socio-economic questions at both household (e.g. number of members, cars, income) and individual (e.g. education, driving license) level were posed.

The same survey was administered through both CATI (Computer Assisted Telephone Interviewing) and CAWI (Computer Assisted Web Interviewing) protocols 7 days a week in three different 4-weeks periods, to control for seasonal effects, to the following samples:

- September-October 2016 (1526 respondents);
- February 2017 (1460 respondents);
- June 2017 (1480 respondents).

4.1. Number of answers and their temporal distribution

The total number of collected interviews was 4’466, among which 402 respondents participated in one or more wave. In particular 166 respondents of the second wave answered also to the first wave of the survey, moreover 236 respondents of the third wave participated also to the second wave, finally 80 interviews belong to all the three waves. Therefore, 4’064 persons were interviewed without any repetition.

Table 4 shows the number of recorded interviews in each wave, which are grouped according to the adopted protocol (CATI or CAWI). In particular, 1’526 interviews were registered in the first wave, 1’460 in the second wave and 1480 in the third wave. Moreover, three-quarters of interviews were collected through CATI protocol (about 76%), whereas one-quarter was collected using CAWI protocol (about 24%). Furthermore, observing Table 4 one can note that these percentages are almost the same for each of the three waves.

Table 4. Number of interviews of each wave and protocol

	I wave		**II wave**		**III wave**		**Total**	
	N	**%**	**N**	**%**	**N**	**%**	**N**	**%**
CATI	1’203	78.8	1’098	75.2	1’089	73.6	3’390	75.9
CAWI	323	21.2	362	24.8	391	26.4	1076	24.1
Total	1’526		1’460		1’480		4’466	

The collected interviews were aggregated according to the number of sections of the survey, which were filled by each respondent; results are grouped by wave and reported in Table 5. Overall, about 78% of the interviewees completed all six sections, moreover the requested minimum threshold of 75% was respected. Only 22 respondents in the first wave decided to interrupt the questionnaire (about 0.5% of the total number of records). The remaining interviewed persons filled only sections A (Introduction), B (Travel diary) and F (Socio-economic characteristics), since registered trips were not a candidate for the other sections due to their attributes. In particular, about 17% of respondents did not perform any trips in the 24 hours before the interview, about 4% carried out trips longer than 50 kilometres and 0.7% reported only trips starting and ending outside the study area presented in section 3.1. Similar percentages were found in each of the three waves.

Table 5. Number of interviews for filled sections of the surveys of each wave

	I wave		II wave		III wave		Total	
	N	%	N	%	N	%	N	%
All	1’128	73.9	1’158	79.3	1’168	78.9	3’454	77.3
A, B and F (no trips)	290	19.0	242	16.6	247	16.7	779	17.4
A, B and F (> 50 km)	67	4.4	50	3.4	61	4.1	178	4.0
A, B and F (ext - ext)	19	1.2	10	0.7	4	0.3	33	0.7
None	22	1.4		0.0		0.0	22	0.5
Total	1’526		1’460		1’480		4’466	

Table 6 reports the average durations of interviews, which are calculated considering the automatically stored starting and ending time of each interview; results are aggregated by wave. Table 6 indicates that web interviews are shorter than telephone interviews, except for the second wave. Since the distributions of percentages of filled sections of the survey are similar among the three waves, the difference of mean duration is not due to the length of the questionnaire (see Table 5). On the other hand, web respondents could stop the survey at any time and restart it later, therefore the longer duration of web interviews might be due to the greater number of paused surveys; since the duration was estimated as the difference between the ending and starting time of each interview, higher evaluated durations were obtained.

Table 6. Average durations of interviews

	I wave	II wave	III wave	Mean
CATI	07:13	07:46	08:55	07:56
CAWI	06:22	20:20	03:06	09:53
Mean	07:03	10:53	07:23	08:24

As previously described, the questionnaire was administered for 7 days a week in three different 4-weeks periods. Table 7 shows the sums of interviews carried out in each day of a week for the two adopted protocols. Considering the distribution of days for the overall sample (last column in Table 7), one can note that the percentages of collected telephone surveys are not uneven, since the interview time was fixed for every day. On the contrary, web version of the questionnaire shows more variations, with a peak on Monday (about 22% of answers) and a minimum on Sunday (about 7%), since persons could perform the interview whenever they wanted. In particular, the percentage of CATI interviews on Sunday was twice the corresponding value for CAWI surveys. Since each respondent had to report trips starting the day before, results suggest that the representativeness of a sample of trips, obtained only from web survey could not be correct, leading to potentially biased results. On the other hand, the present survey adopted two protocols in order to lessen this drawback.

Table 7. Days of administration of the three surveys

		I wave		II wave		III wave		Total	
		N	%	N	%	N	%	N	%
CATI	Monday	154	12.8	157	14.3	134	12.3	445	13.1
	Sunday	104	8.6	149	13.6	165	15.2	418	12.3
	Tuesday	175	14.5	150	13.7	190	17.4	515	15.2
	Wednesday	203	16.9	165	15.0	186	17.1	554	16.3
	Thursday	230	19.1	178	16.2	173	15.9	581	17.1
	Friday	179	14.9	154	14.0	111	10.2	444	13.1
	Saturday	158	13.1	145	13.2	130	11.9	433	12.8
	Total	1’203		1’098		1’089		3’390	
CAWI	Sunday	38	11.8	11	3.0	24	6.1	73	6.8
	Monday	46	14.2	82	22.7	104	26.6	232	21.6
	Tuesday	59	18.3	77	21.3	42	10.7	178	16.5
	Wednesday	28	8.7	43	11.9	56	14.3	127	11.8
	Thursday	22	6.8	61	16.9	65	16.6	148	13.8
	Friday	101	31.3	53	14.6	49	12.5	203	18.9
	Saturday	29	9.0	35	9.7	51	13.0	115	10.7
	Total	323		362		391		1’076	

4.2. Characteristics of the respondents

In this paragraph, the characteristics of interviewees and their households are reported. Since the data under analysis are registered in sections A (Introduction) and F (Socio-economic characteristics), 22 respondents who did not fill these sections were excluded, therefore 4’444 answers were retained for the analysis (see Table 5).

The characteristics reported by respondents at individual level are shown in Table 8. Considering the overall sample (last column of Table 8), the percentages of females and males are very similar (about 48% and 52%, respectively). The average age is 50 years, and about 50% of interviews are aged between 36 and 65 years (see Figure 4). Half of the respondents graduated at high school, about one quarter of them has a Master’s degree or Ph.D., and the remaining part has lower educational levels. Moreover, about 48% of travellers usually work in job locations outside their home, and about 28% of respondents are retired people; Table 8 reports similar values for the number of workers at home, students and unemployed people. The vast majority of respondents (about 82%) owns a driving licence, suggesting a wide use of cars among the population. This aspect is strengthened by the more limited diffusion of subscriptions to public transport and sharing modes. In particular, 21% of respondents has a public transport subscription; furthermore, only 4.3% and 2.5% of interviewees are members of car sharing and bike sharing systems, respectively, since these two services were recently introduced.

Table 8. Characteristics of respondents at individual level

		I wave		II wave		III wave		Total	
		N	**%**	**N**	**%**	**N**	**%**	**N**	**%**
	Totals	1’504		1’460		1’480		4’444	
Gender	Female	774	51.5	760	52.1	767	51.8	2’301	51.8
	Male	730	48.5	700	47.9	713	48.2	2’143	48.2
Age	18-20	49	3.3	64	4.4	64	4.3	177	4.0
	21-24	75	5.0	68	4.7	63	4.3	206	4.6
	25-29	98	6.5	87	6.0	82	5.5	267	6.0
	30-34	120	8.0	109	7.5	110	7.4	339	7.6
	35-44	276	18.4	270	18.5	289	19.5	835	18.8
	45-54	266	17.7	256	17.5	257	17.4	779	17.5
	55-64	215	14.3	211	14.5	217	14.7	643	14.5
	65-74	217	14.4	207	14.2	214	14.5	638	14.4
	More than 75	188	12.5	188	12.9	184	12.4	560	12.6
Educational level	Not high school graduate	392	26.1	364	24.9	373	25.2	1’129	25.4
	High school graduate	806	53.6	733	50.2	738	49.9	2’277	51.2
	Master's degree or Ph.D.	306	20.3	363	24.9	369	24.9	1’038	23.4
Occupational status	Work out of home	720	47.9	678	46.4	749	50.6	2’147	48.3
	Work at home	137	9.1	156	10.7	140	9.5	433	9.7
	Student	107	7.1	123	8.4	111	7.5	341	7.7
	Retired	445	29.6	412	28.2	399	27.0	1’256	28.3
	Unemployed	95	6.3	91	6.2	81	5.5	267	6.0
Licensed driver	Yes	1’225	81.4	1’159	79.4	1’238	83.6	3’622	81.5
	No	279	18.6	301	20.6	242	16.4	822	18.5
Public transport subscription	Yes	291	19.3	318	21.8	320	21.6	929	20.9
	No	1’213	80.7	1’142	78.2	1’160	78.4	3’515	79.1
Car sharing subscription	Yes	61	4.1	57	3.9	71	4.8	189	4.3
	No	1’443	95.9	1403	96.1	1’409	95.2	4’255	95.7
Bike sharing subscription	Yes	43	2.9	26	1.8	40	2.7	109	2.5
	No	1’461	97.1	1’434	98.2	1’440	97.3	4’335	97.5

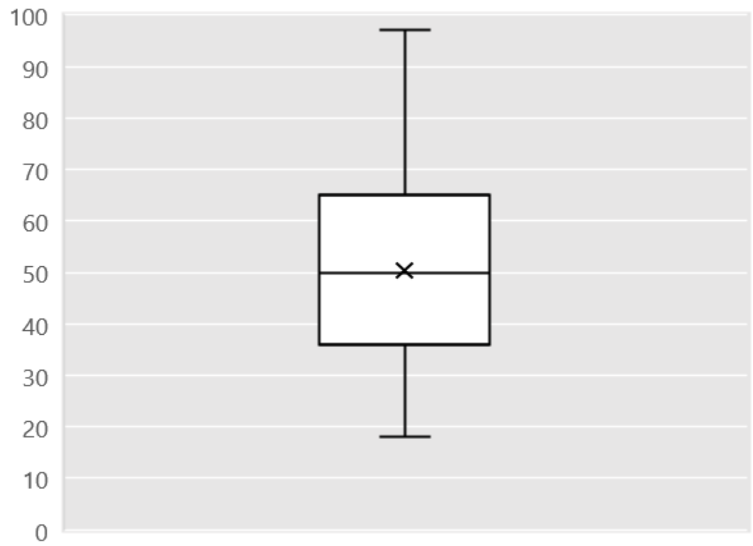

Figure 4. Box plot for age of respondents

Respondents had to declare also usual frequencies of use of several travel modes, in terms of the number of times per week. Results are summarized in Table 9 and represented in Figure 5, which shows percentages values of frequencies for the overall sample. The most frequently adopted means is car as driver, in particular about 44% of interviewees used it more than three times a week, confirming the consideration about car diffusion, explained in the previous paragraph. The second most frequent travel mode is public transport, specifically urban bus (about 17%) and metro (about 8%, a relatively low figure given the fact that only one line is currently operating in Torino). Private car and urban bus show also high values for occasional uses: car is adopted by 18% of respondents and urban bus is adopted by 22%, for one to three times a week. This indicates weak travel habits for some users, who could more easily change their travel means, suggesting a potential penetration of other modes (like car sharing). On the other hand, low frequencies are associated with car sharing and bike sharing, highlighting a rare use. This might be due to either the low diffusion of these modes, or the usage type of them, i.e. not for frequent trips, but only for occasional trips, as registered for taxi and bike.

Table 9. Reported usage frequencies of each travel mode

		I wave		**II wave**		**III wave**		**Total**	
		N	**%**	**N**	**%**	**N**	**%**	**N**	**%**
	Totals	1’504		1’460		1’480		4’444	
Car as driver	More than 3 times a week	662	44.0	581	39.8	696	47.0	1’939	43.6
	From 1 to 3 times a week	271	18.0	248	17.0	286	19.3	805	18.1
	Less than once a week	111	7.4	173	11.8	142	9.6	426	9.6
	Never	460	30.6	458	31.4	356	24.1	1274	28.7
Car as passenger	More than 3 times a week	69	4.6	29	2.0	51	3.4	149	3.4
	From 1 to 3 times a week	187	12.4	207	14.2	236	15.9	630	14.2
	Less than once a week	133	8.8	267	18.3	175	11.8	575	12.9
	Never	1’115	74.1	957	65.5	1’018	68.8	3’090	69.5
Motorbike	More than 3 times a week	53	3.5	29	2.0	36	2.4	118	2.7
	From 1 to 3 times a week	58	3.9	45	3.1	29	2.0	132	3.0

	Less than once a week	36	2.4	41	2.8	35	2.4	112	2.5
	Never	1’357	90.2	1’345	92.1	1’380	93.2	4’082	91.9
Urban bus	More than 3 times a week	282	18.8	233	16.0	260	17.6	775	17.4
	From 1 to 3 times a week	356	23.7	358	24.5	275	18.6	989	22.3
	Less than once a week	289	19.2	348	23.8	241	16.3	878	19.8
	Never	577	38.4	521	35.7	704	47.6	1’802	40.5
School or company bus	More than 3 times a week	16	1.1	9	0.6	23	1.6	48	1.1
	From 1 to 3 times a week	24	1.6	23	1.6	18	1.2	65	1.5
	Less than once a week	31	2.1	34	2.3	30	2.0	95	2.1
	Never	1’433	95.3	1’394	95.5	1’409	95.2	4’236	95.3
Metro	More than 3 times a week	116	7.7	108	7.4	155	10.5	379	8.5
	From 1 to 3 times a week	177	11.8	225	15.4	197	13.3	599	13.5
	Less than once a week	294	19.5	338	23.2	205	13.9	837	18.8
	Never	917	61.0	789	54.0	923	62.4	2’629	59.2
Suburban bus	More than 3 times a week	27	1.8	14	1.0	38	2.6	79	1.8
	From 1 to 3 times a week	42	2.8	33	2.3	47	3.2	122	2.7
	Less than once a week	93	6.2	84	5.8	97	6.6	274	6.2
	Never	1’342	89.2	1’329	91.0	1’298	87.7	3’969	89.3
Train	More than 3 times a week	20	1.3	20	1.4	18	1.2	58	1.3
	From 1 to 3 times a week	38	2.5	44	3.0	42	2.8	124	2.8
	Less than once a week	151	10.0	141	9.7	140	9.5	432	9.7
	Never	1’295	86.1	1’255	86.0	1’280	86.5	3’830	86.2
Taxi	More than 3 times a week	11	0.7	5	0.3	8	0.5	24	0.5
	From 1 to 3 times a week	15	1.0	15	1.0	17	1.1	47	1.1
	Less than once a week	98	6.5	93	6.4	89	6.0	280	6.3
	Never	1’380	91.8	1’347	92.3	1’366	92.3	4’093	92.1
Bike	More than 3 times a week	76	5.1	58	4.0	89	6.0	223	5.0
	From 1 to 3 times a week	122	8.1	103	7.1	82	5.5	307	6.9
	Less than once a week	122	8.1	182	12.5	113	7.6	417	9.4
	Never	1’184	78.7	1’117	76.5	1’196	80.8	3’497	78.7
Bike sharing	More than 3 times a week	13	0.9	9	0.6	16	1.1	38	0.9
	From 1 to 3 times a week	19	1.3	21	1.4	24	1.6	64	1.4
	Less than once a week	32	2.1	30	2.1	44	3.0	106	2.4
	Never	1’440	95.7	1’400	95.9	1’396	94.3	4’236	95.3
Car sharing	More than 3 times a week	15	1.0	6	0.4	11	0.7	32	0.7
	From 1 to 3 times a week	26	1.7	23	1.6	32	2.2	81	1.8
	Less than once a week	51	3.4	61	4.2	67	4.5	179	4.0
	Never	1’412	93.9	1’370	93.8	1370	92.6	4’152	93.4

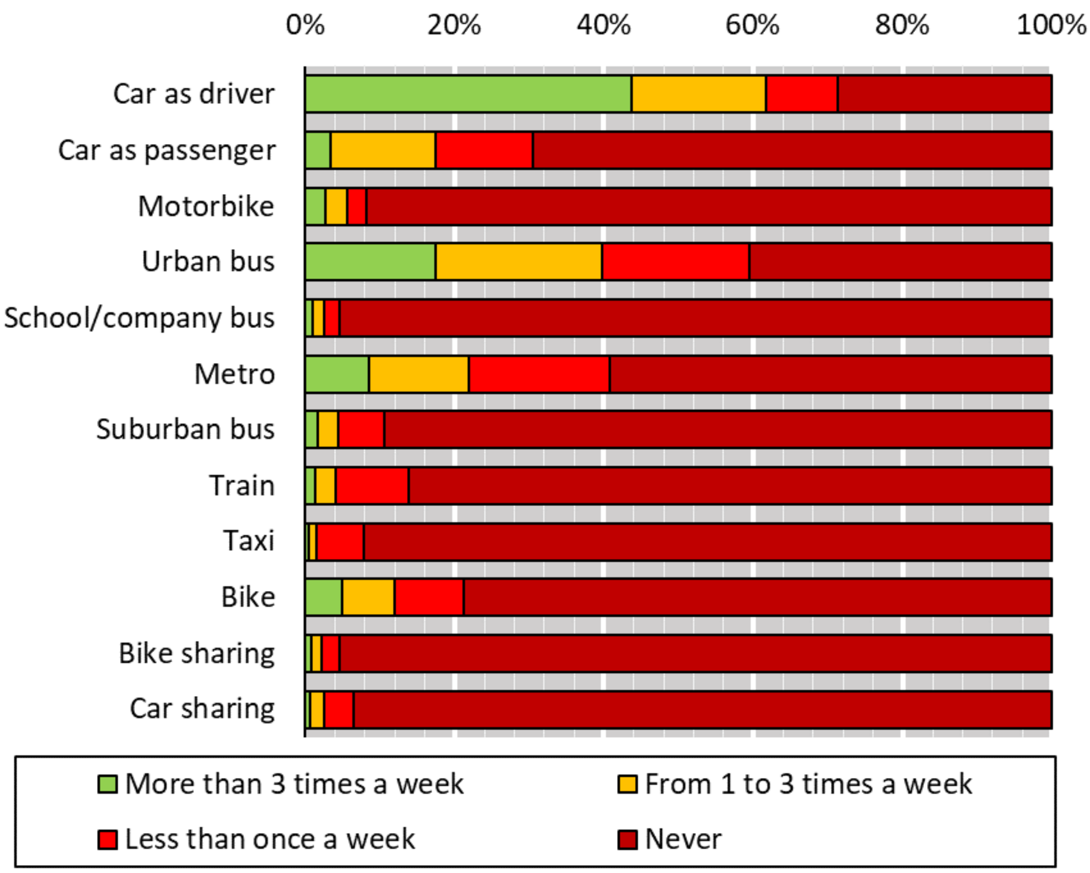

Figure 5. Frequency of use of of each travel mode (percentage values)

Table 10 exhibits socio-economic characteristics reported by respondents considering the household to which they belong. The overall sample of the population reveals that there are many small households, in particular about 65% of them has two or three members, and about 79% has no underage children. The vast majority of respondents lives in households with one or two private cars (about 85%), specifically 44% has one vehicle and 41% has two vehicles, and no motorbike (83%), suggesting that car is the main private motorized means. Considering answers at a disaggregated level, it was estimated that the average number of private cars per household is about 1.4, moreover about 0.8 cars are available for one licensed driver, and each member owned 0.6 cars on average. Lastly, the majority of households has a low-middle monthly income, in particular about 87% of households shows an income between 1’000 and 4’000 euros per month.

Table 10. Socio-economic characteristics at household level

		I wave		II wave		III wave		Total	
		N	**%**	**N**	**%**	**N**	**%**	**N**	**%**
	Totals	1504		1460		1480		4444	
Members	1	184	12.2	222	15.2	248	16.8	654	14.7
	2	556	37.0	551	37.7	582	39.3	1689	38.0
	3	438	29.1	379	26.0	397	26.8	1214	27.3
	4	280	18.6	263	18.0	217	14.7	760	17.1
	5	39	2.6	37	2.5	35	2.4	111	2.5
	More than 5	7	0.5	8	0.5	1	0.1	16	0.4
Workers	0	429	28.5	430	29.5	419	28.3	1278	28.8
	1	299	19.9	360	24.7	363	24.5	1022	23.0
	2	660	43.9	595	40.8	590	39.9	1845	41.5
	3	96	6.4	61	4.2	99	6.7	256	5.8
	More than 3	20	1.3	14	1.0	9	0.6	43	1.0
Underage children	0	1177	78.3	1163	79.7	1188	80.3	3528	79.4
	1	234	15.6	194	13.3	196	13.2	624	14.0
	2	88	5.9	91	6.2	81	5.5	260	5.9
	3	5	0.3	12	0.8	15	1.0	32	0.7
Licensed drivers	0	120	8.0	139	9.5	105	7.1	364	8.2
	1	321	21.3	354	24.2	363	24.5	1038	23.4
	2	675	44.9	639	43.8	703	47.5	2017	45.4
	More than 2	388	25.8	328	22.5	309	20.9	1025	23.1
Owned cars	0	166	11.0	183	12.5	135	9.1	484	10.9
	1	620	41.2	589	40.3	742	50.1	1951	43.9
	2	648	43.1	625	42.8	549	37.1	1822	41.0
	More than 2	70	4.7	63	4.3	54	3.6	187	4.2
Owned motorbikes	0	1214	80.7	1156	79.2	1302	88.0	3672	82.6
	1	267	17.8	273	18.7	162	10.9	702	15.8
	2	21	1.4	30	2.1	16	1.1	67	1.5
	3	2	0.1	1	0.1	0	0.0	3	0.1
Income [€/month]	Less than 1000	97	6.4	116	7.9	92	6.2	305	6.9
	1000-1500	276	18.4	209	14.3	263	17.8	748	16.8
	1500-2000	349	23.2	422	28.9	399	27.0	1170	26.3
	2000-2500	224	14.9	244	16.7	202	13.6	670	15.1
	2500-3000	245	16.3	168	11.5	200	13.5	613	13.8
	3000-4000	206	13.7	195	13.4	240	16.2	641	14.4
	4000-6000	93	6.2	96	6.6	73	4.9	262	5.9
	6000-10000	12	0.8	6	0.4	6	0.4	24	0.5
	More than 10000	2	0.1	4	0.3	5	0.3	11	0.2

Figure 6 displays the number of collected interviews for each Traffic Analysis Zone in the study area. As previously described, the spatial distribution of respondents depends on the adopted sampling plan, which considers the dwelling zone of each interviewee as a stratum.

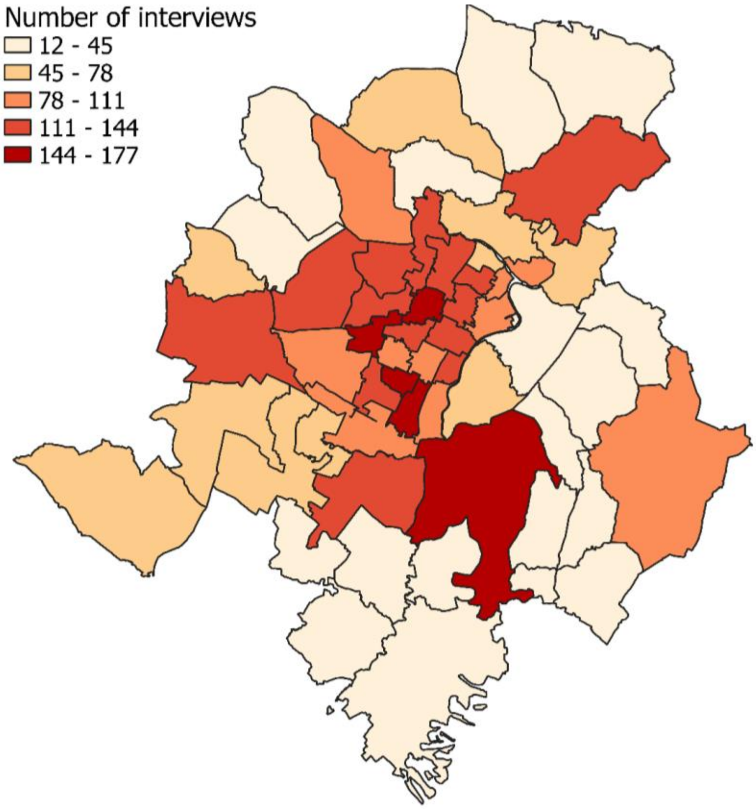

Figure 6. Number of collected interviews for each Traffic Analysis Zone

4.3. Characteristics of registered trips

In this paragraph, trip attributes reported by travellers are reported. Since these data are recorded in section B (Travel diary), 22 respondents who did not fill the section and 779 interviewees who did not perform any trip during the 24 hours before the interview were excluded. Thus, 3'665 answers were retained for a trip level analysis (see Table 5).

4.3.1. Trip sample size: distribution of length, duration and travel purposes

Table 11 summarizes the number of trips carried out by each respondent in the three surveys; the last row contains the total number of collected trips for each wave and for the whole sample. Considering the overall sample, 9'207 trips were registered. More than half of the interviews performed two trips in the 24 hours before the interview (about 57%); moreover, only about 20% of users reported three trips. Using disaggregated data, the number of trips per day performed by each individual was 2.51 on average; this result is similar to the one obtained by the regional mobility agency in 2013 for the same study area (Agenzia per la Mobilità Metropolitana e Regionale, 2015).

Table 11. Number of recorded trips per interviewee

	I wave		II wave		III wave		Total	
	N	**%**	**N**	**%**	**N**	**%**	**N**	**%**
Total	1’214		1’219		1’232		3’665	
1	108	8.9	97	8.0	118	9.6	323	8.8
2	692	57.0	715	58.7	673	54.6	2’080	56.8
3	204	16.8	281	23.1	262	21.3	747	20.4
4	149	12.3	77	6.3	95	7.7	321	8.8
5	33	2.7	26	2.1	48	3.9	107	2.9
6	15	1.2	15	1.2	20	1.6	50	1.4
7	3	0.2	3	0.2	5	0.4	11	0.3
8	2	0.2	1	0.1	3	0.2	6	0.2
9	0	0.0	0	0.0	2	0.2	2	0.1
10	3	0.2	1	0.1	2	0.2	6	0.2
11	1	0.1	0	0.0	0	0.0	1	0.0
12	0	0.0	1	0.1	0	0.0	1	0.0
13	1	0.1	1	0.1	0	0.0	2	0.1
14	3	0.2	1	0.1	4	0.3	8	0.2
Total n. of trips	3’088		2’976		3’143		9’207	

As explained before, in section B (Travel diary) distance of trips was automatically calculated using Google Maps APIs, whereas trip duration was estimated as the difference between the ending time of an activity and the starting time of the subsequent activity. Using these disaggregated data, the distribution of trip lengths and durations were evaluated for the whole sample and represented in Figure 7 and Figure 8, respectively. Half of the trips is shorter than 1 kilometre, whereas about 44% has a distance between 1 and 20 kilometres, and only 6% is longer than 20 kilometres (Figure 7). Moreover, about 70% of trips has a duration between 5 and 30 minutes (Figure 8). The average length of a trip is 5.9 kilometres, whereas the average duration is about 28 minutes. This suggests that most of the trips are urban trips performed on congested roads within the study area.

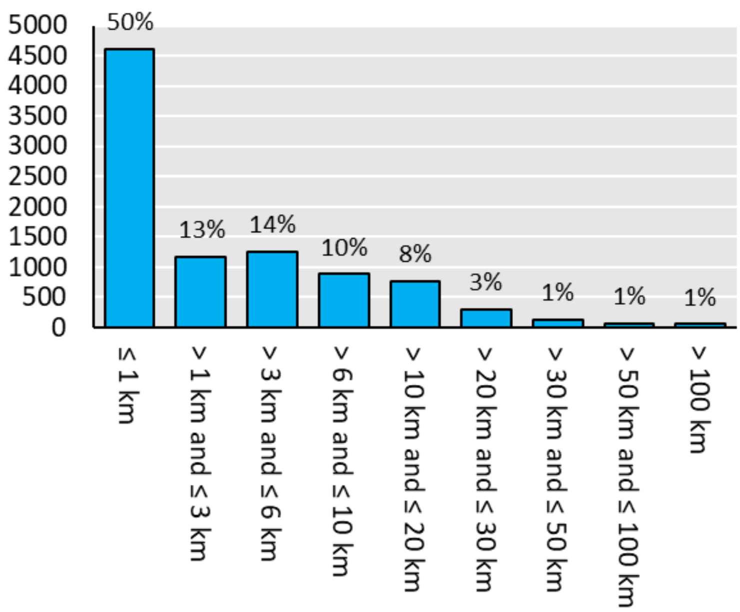

Figure 7. Distribution of trip lengths

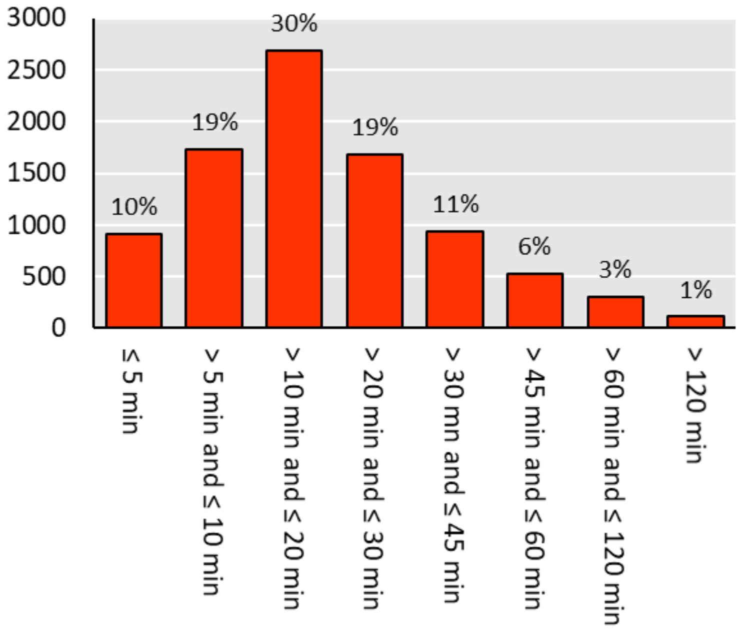

Figure 8. Distribution of trip durations

Considering the characteristics of activities and related trips carried out by all the interviewees, Figure 9 depicts the distribution of starting time of each trip and the type of the related activity performed at the destination of that trip. Figure 9 shows that the morning peak period ranges between 7 and 9 o'clock, when most of trips with a systematic (work or school) and escort purpose are carried out. About 25% of the trips are related to respondents who start their travel to work or school early (from 6 to 7 AM). Moreover, escort trips are performed even after the morning peak period, since several schools are open later (especially nursery schools). The distribution of leisure and shopping trips is almost constant during the day with a peak between 9 and 10 o'clock, and they might be carried out by non-working people. Observing Figure 9, the evening peak period can be identified between 16 and 18 o'clock, when there are many trips to come back home. Other return home trips can be also noted after 10 o'clock until evening, since they are referred to work, school, leisure or shopping locations previously reached.

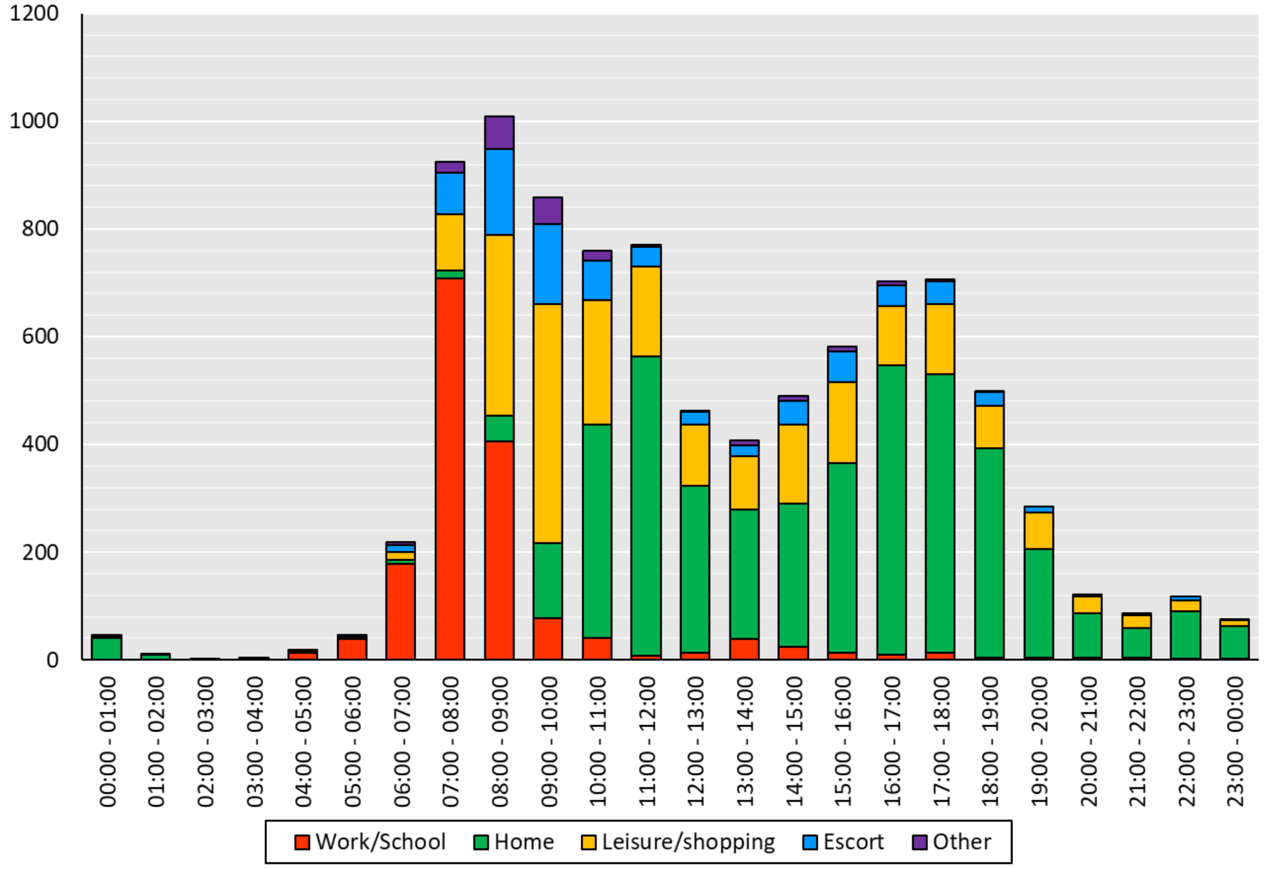

Figure 9. Distribution of starting time of trips and activities performed at destinations

4.3.2. Modal split

Each respondent had to report which travel means she adopted for each trip.

Table 12 shows the number of collected trips with different numbers of transport modes. Observing that table, one can note that the vast majority of trips are unimodal trips; in particular, about 93% of trips in the overall sample was carried out with a single mode, and about 6% with two modes (last column of Table 10). The total number of trips (i.e. the grand total of

Table 12) does not match the previous one (in Table 11), since some respondents did not report the adopted travel mode.

Table 12. Number of adopted travel means for each trip reported by respondents

	I wave		II wave		III wave		Total	
N. of modes	**N**	**%**	**N**	**%**	**N**	**%**	**N**	**%**
1	2'879	94.3	2'695	91.5	2'878	92.8	8'452	92.9
2	143	4.7	199	6.8	162	5.2	504	5.5
3	26	0.9	40	1.4	46	1.5	112	1.2
4	3	0.1	9	0.3	14	0.5	26	0.3
5	0	0.0	2	0.1	1	0.0	3	0.0
6	1	0.0	0	0.0	0	0.0	1	0.0
7 or more	0	0.0	0	0.0	0	0.0	0	0.0
Total	3'052		2'945		3'101		9'098	

Considering the modal share of interviewees in the study area, Table 13 reports the distribution of registered travel means and Figure 10 displays that information for the overall sample. Focusing on the whole number of respondents, the most used travel mode is private car, which accounts for about 48% of the total number of recorded modes. Secondarily, public transport and active modes share similar percentages (around 24%). Among them, urban bus is found in 18% of the trips and walking in 21% of the trips. This indicates that many trips have short distances, since most of them are carried out in an urban context. Sharing modes are used only for 0.5% of the registered trips, highlighting their weak diffusion in the study area; car sharing, in particular, is reported only in 0.2% of the trips.

Table 13. Travel means reported by respondents

		I wave		II wave		III wave		Total	
		N	**%**	**N**	**%**	**N**	**%**	**N**	**%**
Private car	Car as driver	1'378	42.1	1'265	38.2	1'607	47.0	4'250	42.5
	Car as passenger	148	4.5	181	5.5	241	7.1	570	5.7
Public transit	Urban bus	539	16.4	667	20.1	617	18.1	1'823	18.2
	School/company bus	14	0.4	13	0.4	5	0.1	32	0.3
	Metro	101	3.1	186	5.6	139	4.1	426	4.3
	Suburban bus	37	1.1	30	0.9	31	0.9	98	1.0
	Train	33	1.0	28	0.8	29	0.8	90	0.9
Active modes	Walking	742	22.6	740	22.3	595	17.4	2'077	20.8
	Bike	130	4.0	114	3.4	75	2.2	319	3.2
Sharing modes	Bike sharing	11	0.3	11	0.3	9	0.3	31	0.3
	Car sharing	2	0.1	3	0.1	12	0.4	17	0.2
Others	Motorbike	123	3.8	64	1.9	48	1.4	235	2.3
	Taxi	16	0.5	10	0.3	9	0.3	35	0.3
	Airplane	2	0.1	1	0.0	0	0.0	3	0.0
	Ship	1	0.0	2	0.1	0	0.0	3	0.0
Total		3'277		3'315		3'417		10'009	

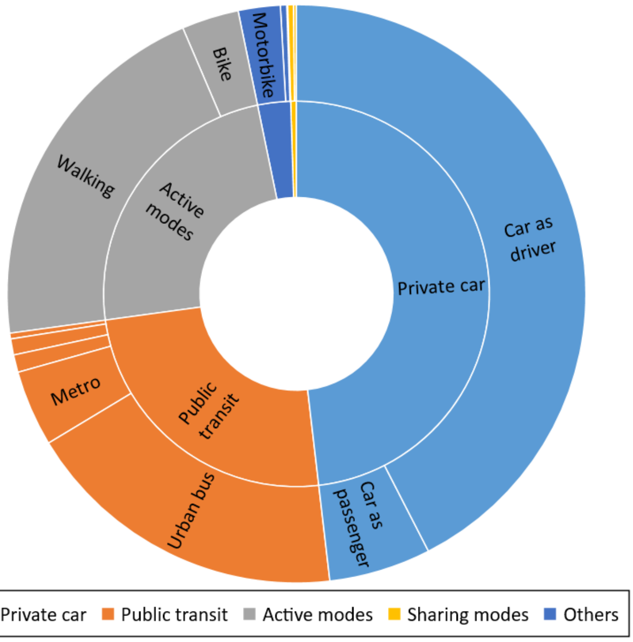

Figure 10. Modal share of respondents of the whole sample

4.3.3. Unimodal trips: modal split, length, duration and purposes

Since the vast majority of collected trips are unimodal, the following analysis considers only these trips. Using disaggregated data, it was estimated that each respondent performs about 2.43 unimodal trips per day; furthermore, the average number of unimodal motorized and non-motorized trips per day are 2.26 and 1.97, respectively. Table 14 and Figure 11 show the number of travel means, recorded for unimodal trips in the entire sample. Observing these two elements one can note that private car is the most used mode (about 54%). Secondly, unlike results in Table 13 and Figure 10, active modes account for 25% of the trips (in particular bike), moreover public transport trips are about 18%. Whereas similar percentages are obtained for sharing modes, like car sharing (0.2%).

Table 14. Travel means for unimodal trips in the whole sample

		N	%
Private car	Car as driver	4’039	47.8
	Car as passenger	543	6.4
Public transit	Urban bus	1’248	14.8
	School/company bus	16	0.2
	Metro	176	2.1
	Suburban bus	39	0.5
	Train	31	0.4
Active modes	Walking	1’794	21.2
	Bike	302	3.6
Sharing modes	Bike sharing	17	0.2
	Car sharing	13	0.2
Others	Motorbike	211	2.5
	Taxi	22	0.3
Total		8’452	

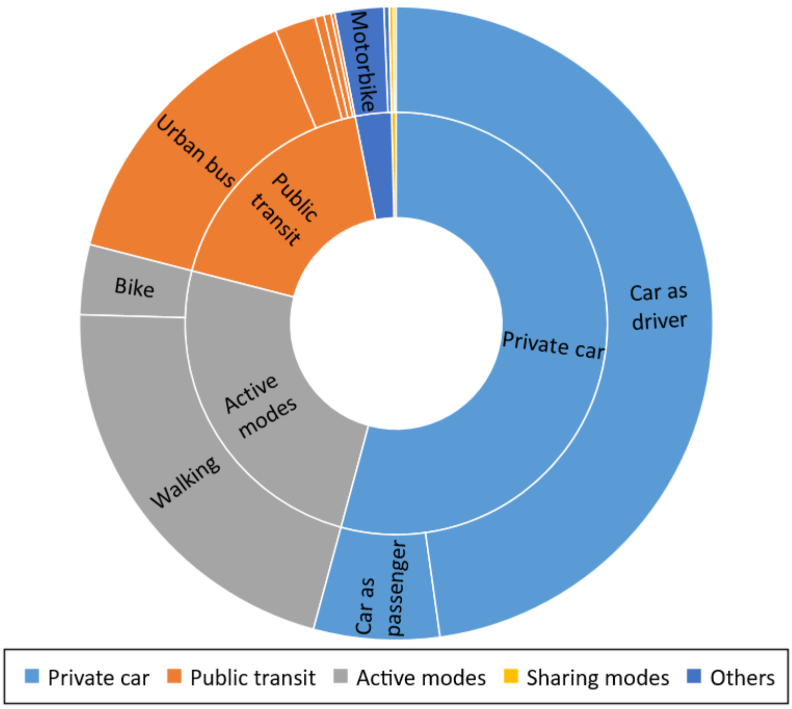

Figure 11. Modal share for unimodal trips of the whole sample

The distribution of trip lengths and duration was analysed considering also the mode adopted by respondents. Results are exhibited in Figure 12 and Figure 13, which show trip distances, and Figure 14 and Figure 15, which display trip durations. Observing the two first figures one can note that private car is used for most of the trip lengths, in particular for distances greater than 6 kilometres. Moreover, public transport is chosen for a wide range of trip length, with similar percentage values. As expected, the majority of walking trips are shorter than 3 kilometres; whereas, bike and bike sharing are mostly adopted for trips up to 6 kilometres. On the other hand, Figure 14 and Figure 15 indicate that trips on private car cover all the range of durations, even if most of them last from 5 to 30 minutes. Public transport trips tend to be longer than 10 minutes and the majority of them has a duration ranging from 10 to 30 minutes. Most of walking trips are carried out with a duration shorter than 20 minutes. In conclusion, private car seems to be adopted for a wide range of distances, like public transport, but with shorter duration, whereas walking and bike are used for very short trips.

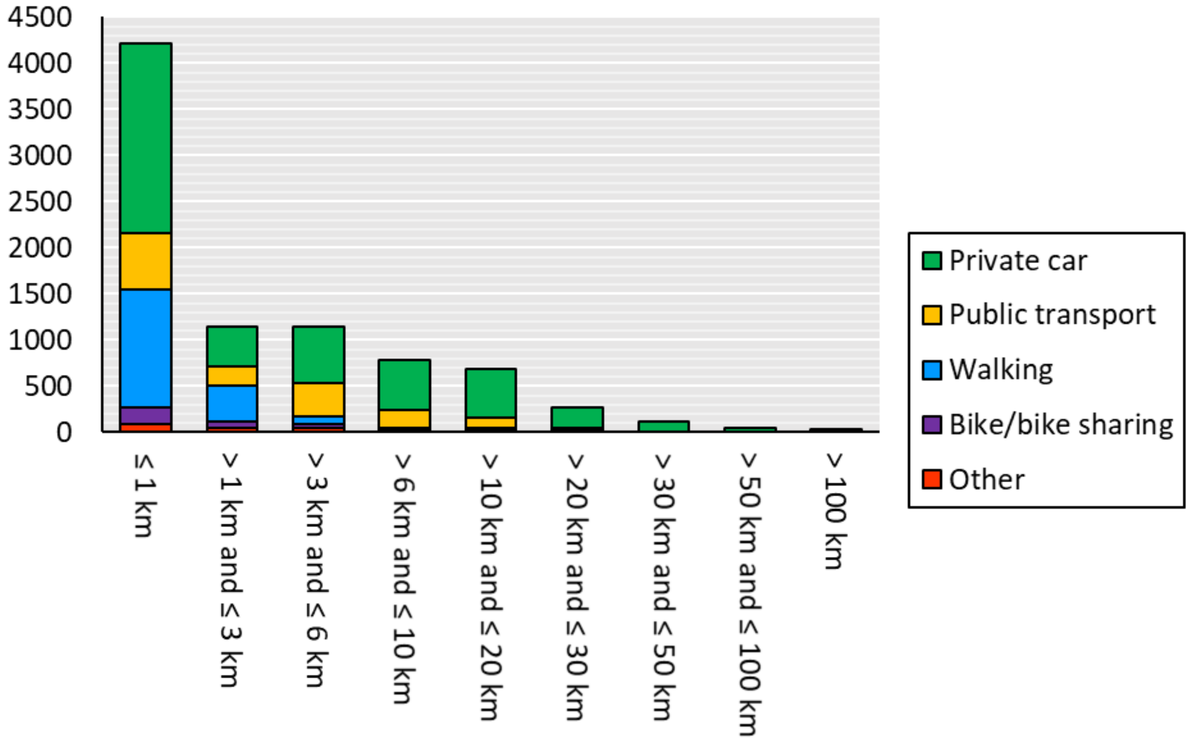

Figure 12. Distribution of trip lengths considering different travel modes (absolute values)

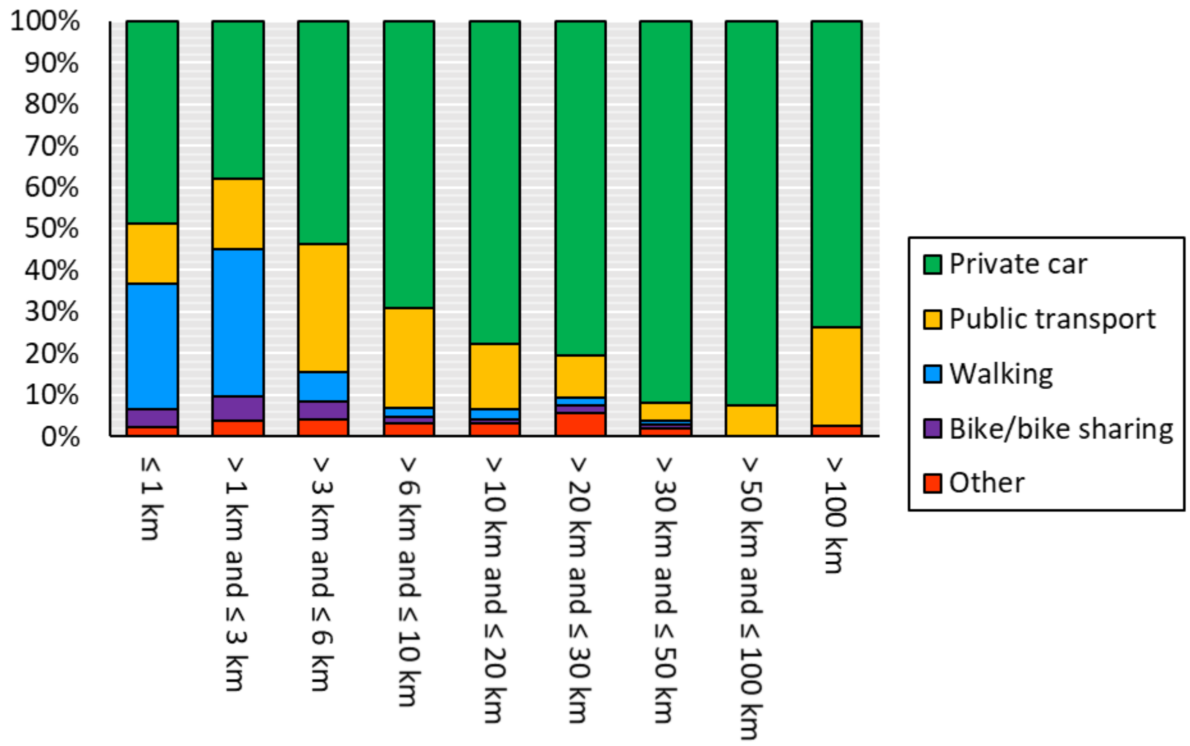

Figure 13. Distribution of trip lengths considering different travel modes (percentage values)

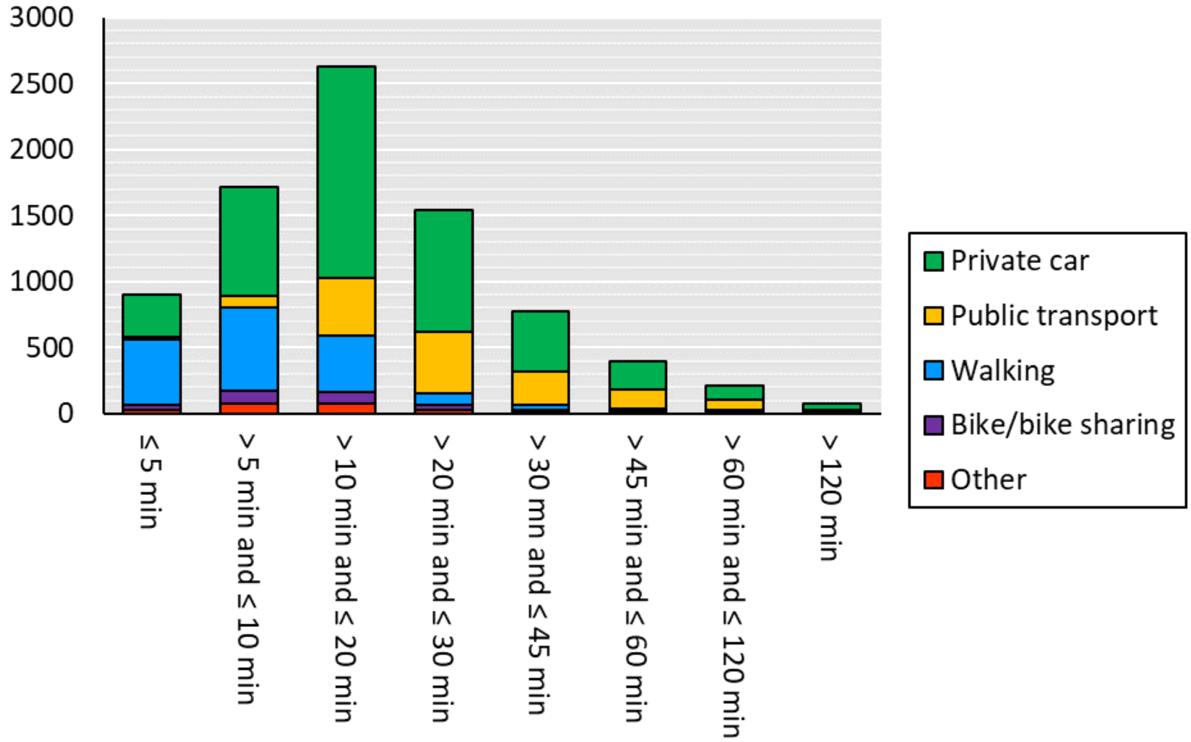

Figure 14. Distribution of trip durations (absolute values)

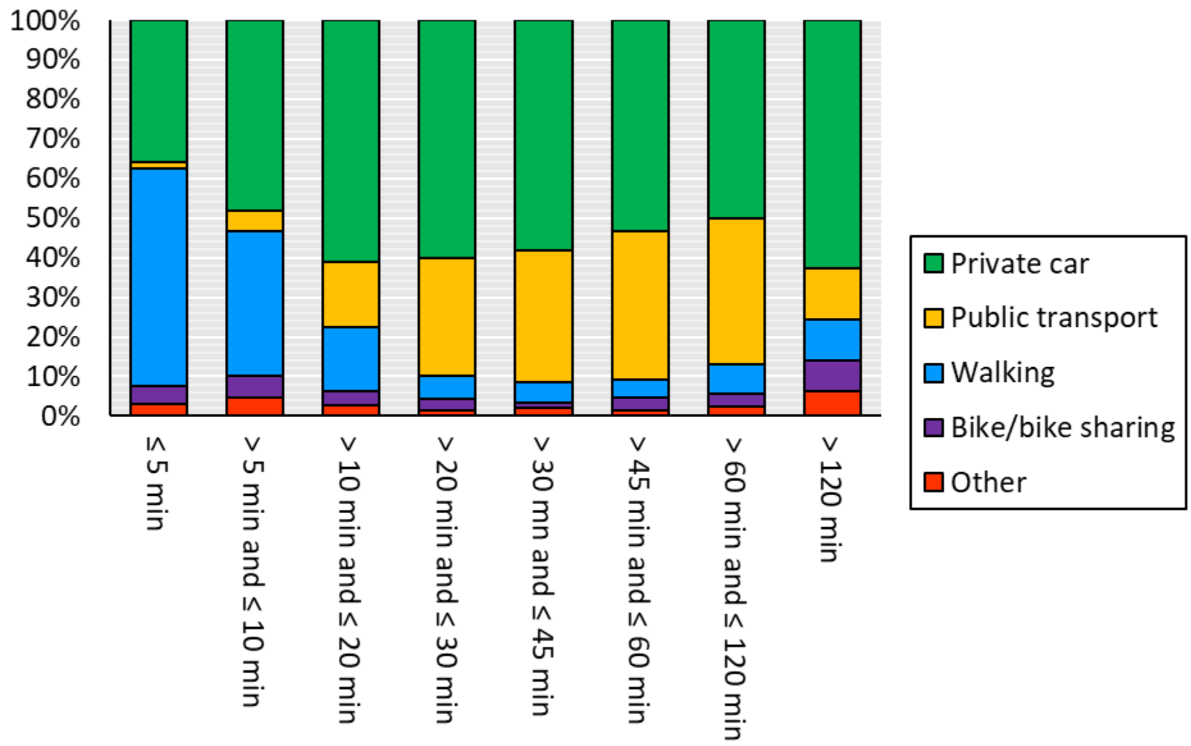

Figure 15. Distribution of trip durations (percentage values)

Figure 16. Number of unimodal trips per travel purpose and modes (absolute values)

Figure 16 and Figure 17 represent absolute and percentage values of unimodal trips performed by respondents, considering different activities carried out at the destination of each trip. These two figures show that, excluding return to home trips, private car is most adopted for systematic (work or school), leisure and escorting trips, since it provides great flexibility. Secondarily, public transport is chosen for both mandatory and leisure trips, but not for escorting trips, probably because of its scheduled frequency which does not ensure enough flexibility. The majority of trips on active modes (walking and bike) are leisure or shopping trips, since they do not require any time pressure, which could induce to choose faster travel means.

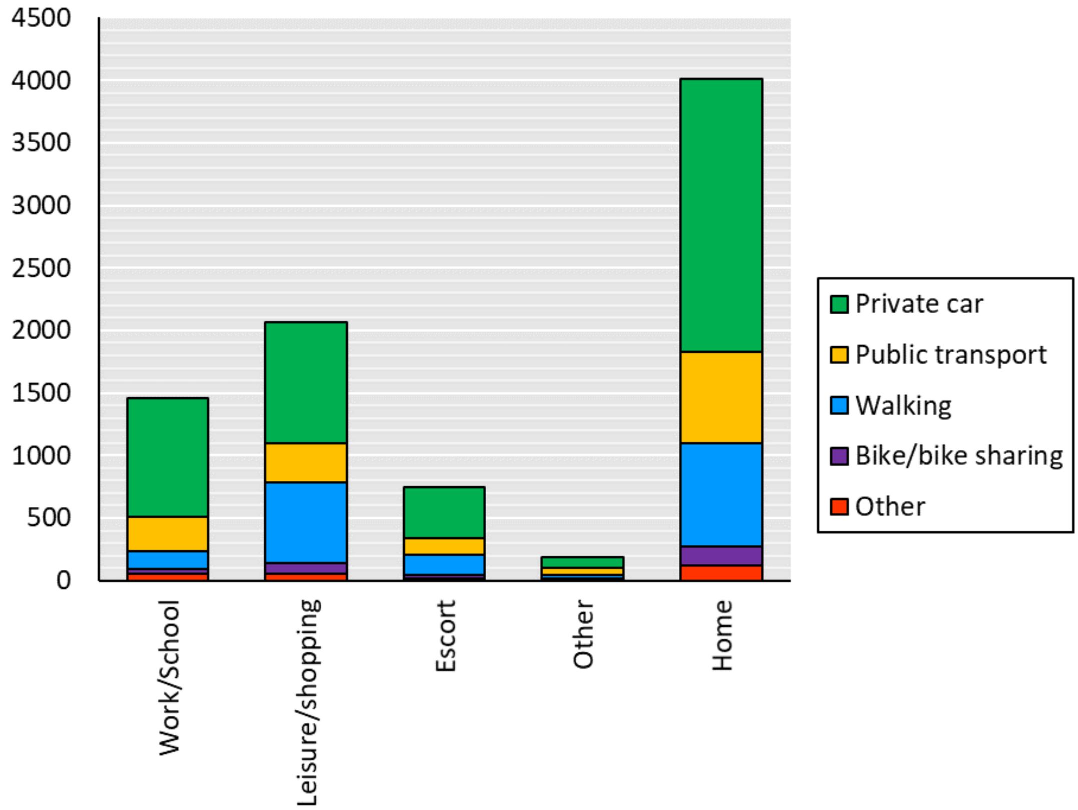

Figure 16. Number of unimodal trips per travel purpose and modes (absolute values)

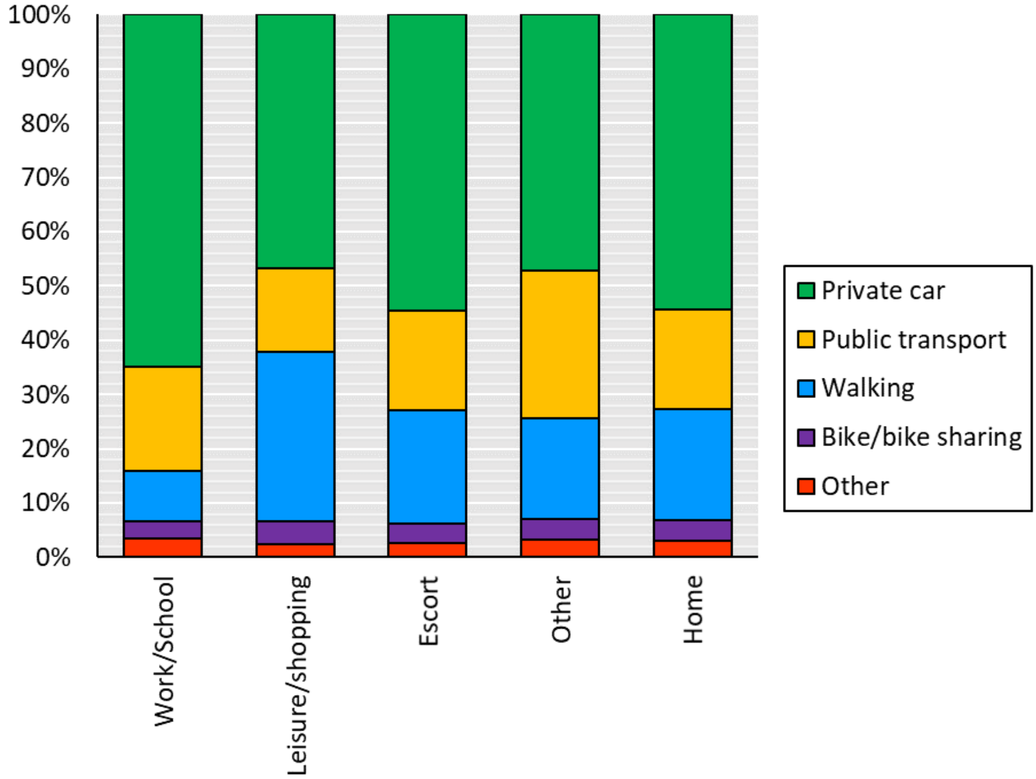

Figure 17. Number of unimodal trips per travel purpose and mode (percentage values)

4.4. Profiling car sharing members

In order to analyse characteristics and travel habits of car sharing members, interviewees who reported to own a car sharing subscription were selected; thus, 189 answers (about 4.3% of the whole sample) are retained. Attributes of car sharing users, both at individual and household level, and use frequencies of different travel means are compared with those of the overall sample and with those of the fraction of the sample living within the service area of at least one car sharing operator. In fact, service areas are not including some of the more peripheral areas of the city, thus the socioeconomic characteristics of the people living there may differ from those of the whole population. Table 15 displays the characteristics of these three samples at individual level. The sample of respondents living in the operating area has similar characteristics of those of the whole sample. The majority of car sharing users (about 62%) became a member of the system from 6 months up to 2 years before the interview time, since several car sharing operators were introduced in Turin from 2015 to 2016. Figure 19 shows the spatial distribution of locations of residences of interviewed car sharing members. In particular, the thick red line delimits the union of the service areas of all the three car sharing operators, whereas Traffic Analysis Zones belonging to the study area are marked using a black line. On the other hand, green points represent the home locations of car sharing members, whereas the colour intensity of each zone represents the density of interviewed members living in that zone. Observing Figure 19, one can note that most of the car sharing members (around 86%) lives in the service area of at least one car sharing operator. The distribution of males and females differs among the three samples; in particular, the proportion of male car sharing members is greater than the corresponding proportions of the whole population (χ^2 = 6.4804, p-value < 0.05) and the sample living in the operating area (χ^2 = 4.5159, p-value < 0.05). Unlike the other two samples, the majority (77%) of car sharing members has an age between 25 to 54 years, and half of them is aged more than 29 and less than 48 years (Figure 18). Both the whole sample and the sample in the operating area show an interquartile range of age which is wider than the one of car sharing members (Figure 18). Furthermore, the median of members' age is 36, which is significantly lower than that of the entire population (50, Mann-Whitney-Wilcoxon = 267'470, p-value < 0.01) and that of the sample living in the operating area (48, Mann-Whitney-Wilcoxon = 152'367, p-value < 0.01), like in previous studies. Moreover, the proportion of retired people among members is lower than the one of the entire population (5% against 28%). Like in previous works, car sharing members tend to have a higher education; in particular the number of members owning a Master's Degree or a Ph.D. is twice the corresponding numbers of the whole sample (χ^2 = 94.044, p-value < 0.01) and the subsample in the operating area (χ^2 = 69.422, p-value < 0.01). Lastly, a higher percentage of car sharing users own a public transport subscription; in particular the proportion of public transport subscribers is about 39% among car sharing members, 27% among the total number of interviews sample (χ^2 = 33.583, p-value < 0.01) and 21% among residents in the operating area sample (χ^2 = 10.147, p-value < 0.01). Similar results are obtained for bike sharing subscription; specifically, 28% of car sharing members are also bike sharers, whereas only 3% of the entire population (χ^2 = 351.81, p-value < 0.01) and 4% of those living in the operating area (χ^2 = 178.91, p-value < 0.01) have a bike sharing subscription.

Table 15. Socio-economic at individual level of the whole sample, the portion living in the operating area and car sharing members

		Whole sample		**Sample living in operating area**		**Car sharing members**	
		N	**%**	**N**	**%**	**N**	**%**
Gender	Female	2’301	51.8	1’187	50.4	80	42.3
	Male	2’143	48.2	1’170	49.6	109	57.7
Age	18-20	177	4.0	114	4.8	3	1.6
	21-24	206	4.6	124	5.3	14	7.4
	25-29	267	6.0	150	6.4	32	16.9
	30-34	339	7.6	201	8.5	34	18.0
	35-44	835	18.8	469	19.9	49	25.9
	45-54	779	17.5	376	16.0	31	16.4
	55-64	643	14.5	318	13.5	19	10.1
	65-74	638	14.4	318	13.5	7	3.7
	More than 75	560	12.6	287	12.2	0	0.0
Educational level	Not high school graduate	1’129	25.4	542	23.0	13	6.9
	High school graduate	2’277	51.2	1’199	50.9	76	40.2
	Master's degree or Ph.D.	1’038	23.4	616	26.1	100	52.9
Occupational status	Work out of home	2’147	48.3	1’173	49.8	140	74.1
	Work at home	433	9.7	207	8.8	8	4.2
	Student	341	7.7	213	9.0	23	12.2
	Retired	1’256	28.3	623	26.4	10	5.3
	Unemployed	267	6.0	141	6.0	8	4.2
Licensed driver	Yes	3’622	81.5	1’886	80.0	189	100.0
	No	822	18.5	471	20.0	0	0.0
PT subscription	Yes	929	20.9	654	27.7	73	38.6
	No	3’515	79.1	1’703	72.3	116	61.4
Bike sharing subscription	Yes	109	2.5	98	4.2	53	28.0
	No	4’335	97.5	2’259	95.8	136	72.0
Car sharing subscription	Yes	189	4.3	163	6.9	189	100.0
	No	4’255	95.7	2’194	93.1	0	0.0
Car sharing time membership	Less than 1 month	-	-	-	-	13	6.9
	From 1 up to 6 months	-	-	-	-	32	16.9
	From 6 months up to 1 year	-	-	-	-	43	22.8
	From 1 up to 2 years	-	-	-	-	74	39.2
	More than 2 years	-	-	-	-	27	14.3
Residence in OA	Yes	2’357	53.0	2’357	100.0	163	86.2
	No	2’087	47.0	0	0.0	26	13.8

Notes: PT: public transport; OA: operating area

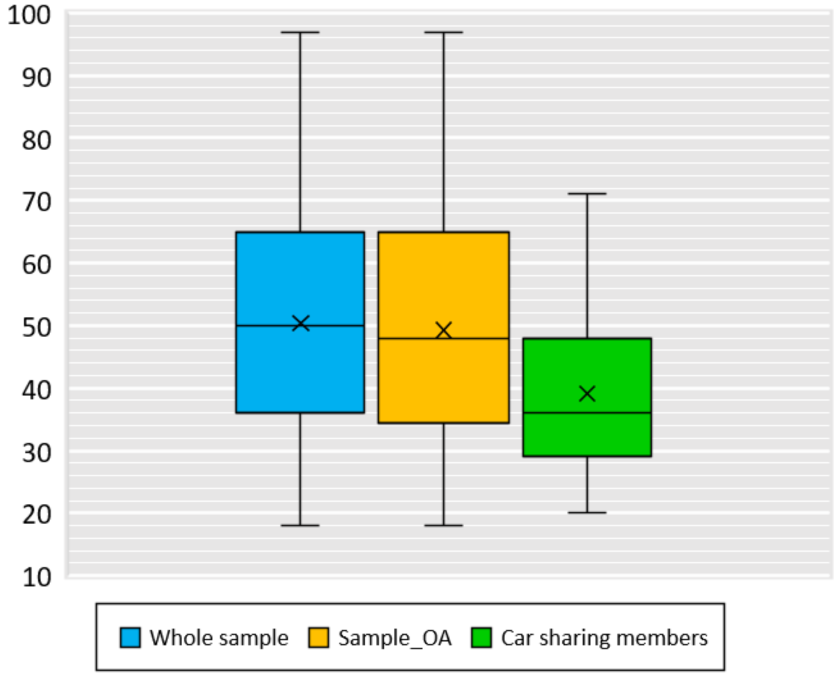

Figure 18. Box plots of distribution of age of the whole sample, the portion living in the operating area and car sharing members

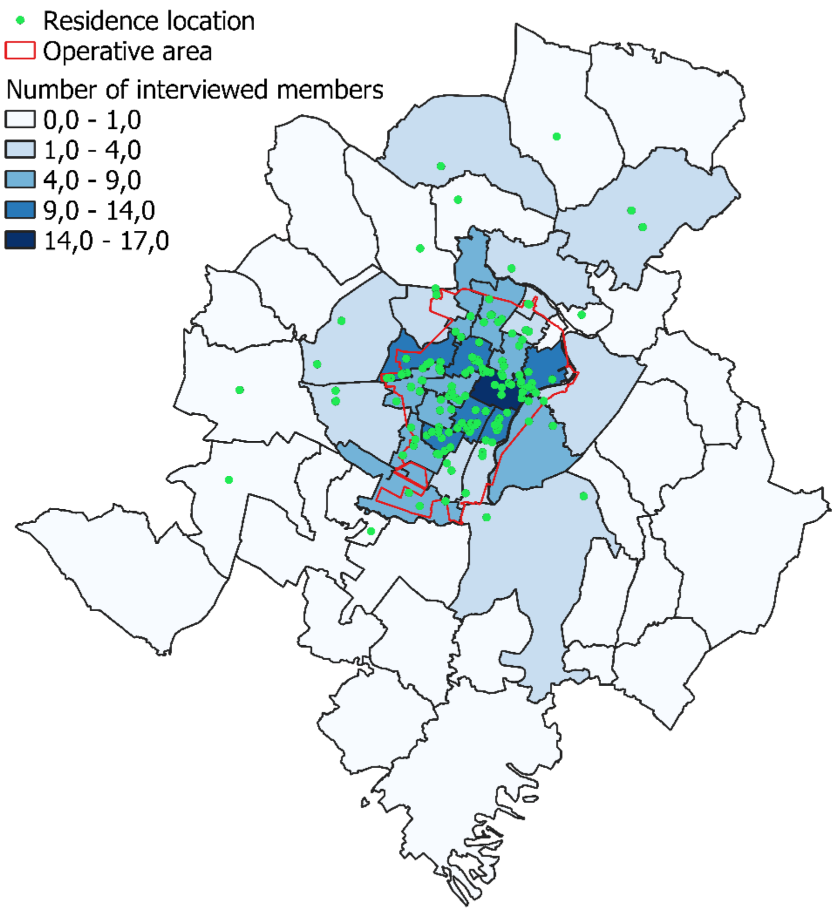

Figure 19. Operating area and residence locations of interviewed car sharing members

Like in the previous case, Table 16 indicates that socio-economic characteristics at household level do not significantly change between the whole population and the sample living in the operating area. Moreover, the distribution of household members, workers and underage children is similar in the three datasets. On the contrary, the average number of licensed drivers in each household is slightly greater for households with a car sharing member; in particular, members live in households with about 2.02 drivers, whereas households in the study area and in the operating area have about 1.83 (Mann-Whitney-Wilcoxon = 462'910, p-value < 0.01) and 1.79 (Mann-Whitney-Wilcoxon = 251'700, p-value < 0.01) drivers, respectively. Unlike previous studies, the variation of the average number of owned cars is not statistically significant among the three datasets. Furthermore, Table 16 shows that households of car sharing members have more dispersed income level, with a greater median (about 2'250€) rather than those of the whole population (1'900€, Mann-Whitney-Wilcoxon = 489'342, p-value < 0.01) and the subsample living in the operating area (1'900€, Mann-Whitney-Wilcoxon = 258'507, p-value < 0.01).

Table 16. Socio-economic characteristics at household level of the whole sample, the portion living in the operating area and car sharing members

		Whole sample		**Sample living in operating areas**		**Car sharing members**	
		N	**%**	**N**	**%**	**N**	**%**
	Totals	4'444		2'357		189	
Members	1	654	14.7	398	16.9	35	18.5
	2	1'689	38.0	875	37.1	65	34.4
	3	1'214	27.3	643	27.3	46	24.3
	4	760	17.1	365	15.5	39	20.6
	5	111	2.5	68	2.9	1	0.5
	More than 5	16	0.4	8	0.3	3	1.6
Workers	0	1'278	28.8	655	27.8	11	5.8
	1	1'022	23.0	548	23.2	63	33.3
	2	1'845	41.5	992	42.1	93	49.2
	3	256	5.8	137	5.8	13	6.9
	More than 3	43	1.0	25	1.1	9	4.8
Underage children	0	3'528	79.4	1'908	81.0	140	74.1
	1	624	14.0	307	13.0	38	20.1
	2	260	5.9	118	5.0	11	5.8
	3	32	0.7	24	1.0	0	0.0
Licensed drivers	0	364	8.2	208	8.8	43	22.8
	1	1'038	23.4	587	24.9	98	51.9
	2	2'017	45.4	1'049	44.5	48	25.4
	More than 2	1'025	23.1	513	21.8	0	0.0
Owned cars	0	484	10.9	306	13.0	23	12.2
	1	1'951	43.9	1'097	46.5	79	41.8
	2	1'822	41.0	880	37.3	76	40.2
	More than 2	187	4.2	74	3.1	11	5.8
Owned motorbikes	0	3'672	82.6	1'935	82.1	135	71.4
	1	702	15.8	383	16.2	46	24.3
	2	67	1.5	37	1.6	8	4.2

	3	3	0.1	2	0.1	0	0.0
Income [€/month]	Less than 1’000	305	6.9	179	7.6	12	6.3
	1’000-1’500	748	16.8	389	16.5	28	14.8
	1’500-2’000	1’170	26.3	591	25.1	27	14.3
	2’000-2’500	670	15.1	353	15.0	32	16.9
	2’500-3’000	613	13.8	325	13.8	26	13.8
	3’000-4’000	641	14.4	376	16.0	36	19.0
	4’000-6’000	262	5.9	128	5.4	23	12.2
	6’000-10’000	24	0.5	11	0.5	3	1.6
	More than 10’000	11	0.2	5	0.2	2	1.1

Table 17 and Figure 20 report the frequencies of use of different travel modes for the three datasets. Observing these two elements, one can note that the majority of car sharing members (about 64%) use shared vehicles only occasionally; moreover, about 33% of them indicated to have never use the service. This suggests that car sharing is not adopted for systematic trips. Furthermore, car sharing members drive a private car more often rather than the whole sample ($\chi^2 = 4.3531$, p-value < 0.05) and than those living in the operating area ($\chi^2 = 18.183$, p-value < 0.01). Similarly, car sharers show more frequent use of urban bus respect to the whole population ($\chi^2 = 5.9186$, p-value < 0.01). This might be caused by the different travel habits of the two samples, i.e. interviews living in the service area usually perform shorter urban trips which are suitable for urban buses, conversely, respondents belonging to the whole sample carry out longer trips since some of them lives outside the central area, therefore, using urban buses less. Overall, car sharing members use public transport more often than the other two groups. In particular, the proportion of the whole population that never adopts metro is three times the corresponding value of car sharing members (59% against 30%). Moreover, the proportion of car sharer using frequently bike is significantly higher rather than the entire sample ($\chi^2 = 30.502$, p-value < 0.01) and respondents living in the operating area ($\chi^2 = 18.967$, p-value < 0.01). Similarly, car sharing members show a higher usage frequency rather than the two other datasets, even if only for occasional trips; in particular, about 30% of car sharing subscribers use bike sharing three times or less a week, whereas the corresponding value for all the respondents is about 4%.

Table 17. Usage frequencies of each travel mode for the whole sample, the portion living in the operating area and car sharing members

		Whole sample		**Sample living in operating areas**		**Car sharing members**	
		N	**%**	**N**	**%**	**N**	**%**
	Totals	4’444		2’357		189	
Car as driver	More than 3 times a week	1’939	43.6	843	35.8	97	51.3
	From 1 to 3 times a week	805	18.1	457	19.4	41	21.7
	Less than once a week	426	9.6	279	11.8	21	11.1
	Never	1’274	28.7	778	33.0	30	15.9
Car as passenger	More than 3 times a week	149	3.4	78	3.3	14	7.4
	From 1 to 3 times a week	630	14.2	327	13.9	39	20.6
	Less than once a week	575	12.9	339	14.4	49	25.9
	Never	3’090	69.5	1’613	68.4	87	46.0
Motorbike	More than 3 times a week	118	2.7	70	3.0	10	5.3

	From 1 to 3 times a week	132	3.0	88	3.7	19	10.1
	Less than once a week	112	2.5	71	3.0	20	10.6
	Never	4’082	91.9	2’128	90.3	140	74.1
Urban bus	More than 3 times a week	775	17.4	560	23.8	46	24.3
	From 1 to 3 times a week	989	22.3	614	26.1	47	24.9
	Less than once a week	878	19.8	498	21.1	56	29.6
	Never	1’802	40.5	685	29.1	40	21.2
School or company bus	More than 3 times a week	48	1.1	26	1.1	6	3.2
	From 1 to 3 times a week	65	1.5	43	1.8	10	5.3
	Less than once a week	95	2.1	59	2.5	15	7.9
	Never	4’236	95.3	2’229	94.6	158	83.6
Metro	More than 3 times a week	379	8.5	279	11.8	31	16.4
	From 1 to 3 times a week	599	13.5	377	16.0	62	32.8
	Less than once a week	837	18.8	510	21.6	58	30.7
	Never	2’629	59.2	1’191	50.5	38	20.1
Suburban bus	More than 3 times a week	79	1.8	33	1.4	7	3.7
	From 1 to 3 times a week	122	2.7	57	2.4	16	8.5
	Less than once a week	274	6.2	177	7.5	44	23.3
	Never	3’969	89.3	2’090	88.7	122	64.6
Train	More than 3 times a week	58	1.3	25	1.1	4	2.1
	From 1 to 3 times a week	124	2.8	82	3.5	24	12.7
	Less than once a week	432	9.7	305	12.9	71	37.6
	Never	3’830	86.2	1’945	82.5	90	47.6
Taxi	More than 3 times a week	24	0.5	11	0.5	4	2.1
	From 1 to 3 times a week	47	1.1	40	1.7	4	2.1
	Less than once a week	280	6.3	188	8.0	58	30.7
	Never	4’093	92.1	2’118	89.9	123	65.1
Bike	More than 3 times a week	223	5.0	143	6.1	27	14.3
	From 1 to 3 times a week	307	6.9	180	7.6	30	15.9
	Less than once a week	417	9.4	232	9.8	31	16.4
	Never	3’497	78.7	1’802	76.5	101	53.4
Bike sharing	More than 3 times a week	38	0.9	26	1.1	10	5.3
	From 1 to 3 times a week	64	1.4	56	2.4	21	11.1
	Less than once a week	106	2.4	76	3.2	35	18.5
	Never	4’236	95.3	2’199	93.3	123	65.1
Car sharing	More than 3 times a week	32	0.7	18	0.8	7	3.7
	From 1 to 3 times a week	81	1.8	65	2.8	39	20.6
	Less than once a week	179	4.0	130	5.5	81	42.9
	Never	4’152	93.4	2’144	91.0	62	32.8

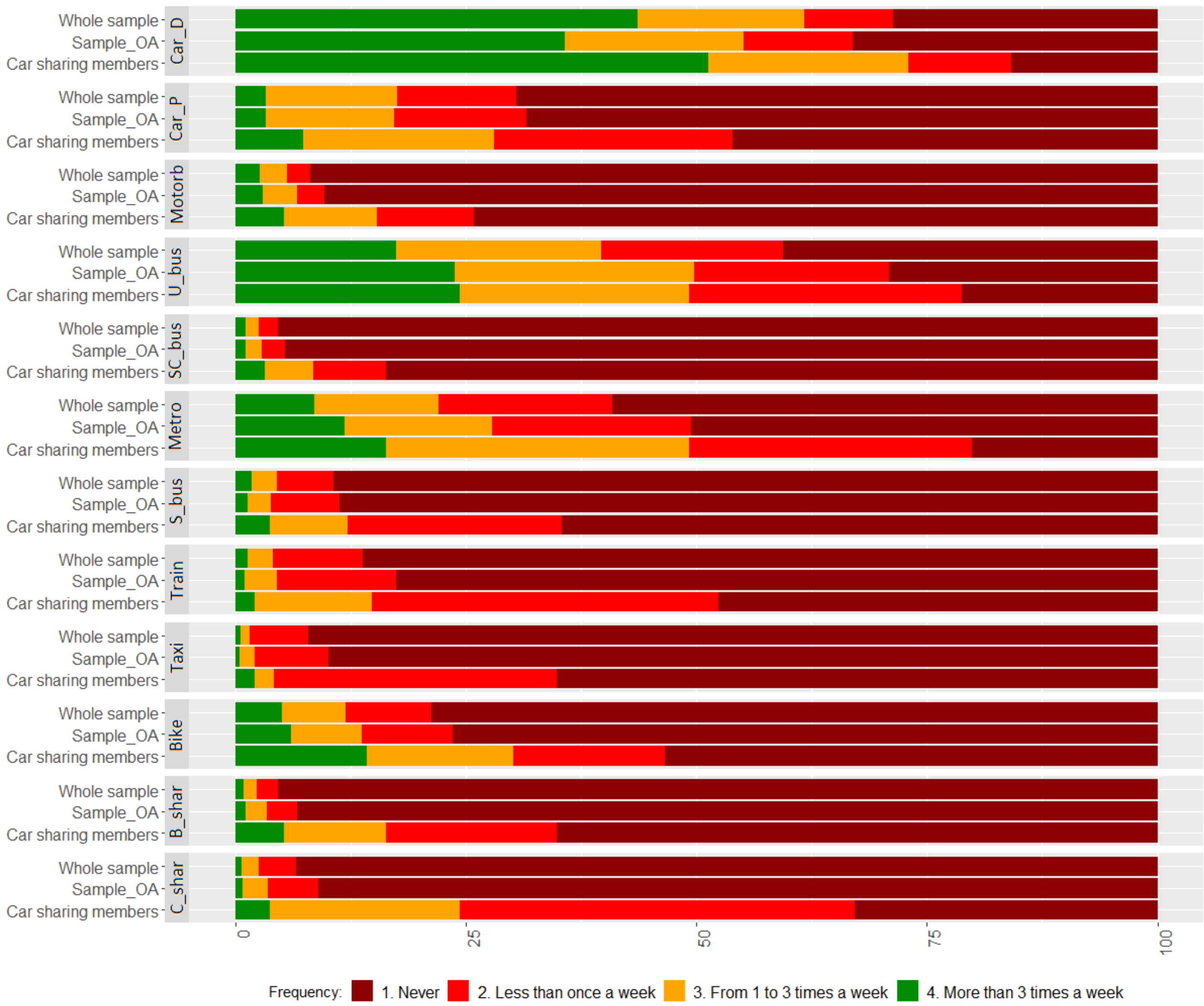

Figure 20. Percentages of use reported use frequencies of each travel mode for the whole sample, the portion living in the operating area (Sample_OA) and car sharing members. [Car_D. car as driver, Car_P: car as passenger; Motorb: motorbike; U_bus: urban bus; SC_bus: school/company bus; Metro: metro; S_bus: suburban bus; Train: train; Bike: bike; B_shar: bike sharing; C_shar: car sharing]

In conclusion, comparing socio-economic characteristics and travel habits of car sharing members to those of the whole population and a subsample living in at least one operating area, car sharing members tend to be male, younger, with a higher level of education and multimodal. Moreover, they live in household with a higher number of licensed drivers and a higher income level. Concerning travel habits of subscribers, they use private car, public transport, bike and bike sharing more often, suggesting a multimodal behaviour.

4.5. Macro-Trip level analysis

In this section, answers to questions about the selected macro-trip are analysed (see Appendix A for a definition of the macro-trip). Since data are contained in sections C (Focus on a specific trip chain), D (Attitudinal survey) and E (Stated-preferences experiments), only respondents who fill these parts are considered; therefore, 3'454 interviews are retained for the analysis.

As reported in Table 18, the majority of respondents, whose macro-trip was selected, performed that trip chain more than once a week; in particular, about 44% reported a weekly frequency of more than three times and around 34% declared a frequency ranging from one to three times. Consequently, these interviews did not carry out the macro-trip occasionally, therefore their answers can be considered reliable, since they are based on a usually experienced trip.

Table 18. Reported frequency of the macro-trip

	I wave		II wave		III wave		Total	
	N	%	N	%	N	%	N	%
More than 3 times a week	578	51.2	463	39.9	467	40.0	1'508	43.7
From 1 to 3 times a week	369	32.7	377	32.5	414	35.5	1'160	33.6
Less than once a week	157	13.9	234	20.2	228	19.5	619	17.9
Never	24	2.1	85	7.3	58	5.0	167	4.8
	1'128		1'159		1'167		3'454	

Moreover, Table 19 shows the number of transport modes on which respondents declared to have travelled for the majority of the trip chain duration. Comparing Table 19 with the corresponding results for the whole representative sample reported in Table 13, one can note that the two distributions of adopted transport modes are very similar, strengthening the basis for an analysis of modal share considering only the selected macro-trips.

Table 19. Number of adopted travel means by respondents for each selected macro-trip

		I wave		II wave		III wave		Total	
		N	%	N	%	N	%	N	%
Private car	Car as driver	505	44.8	484	41.8	575	49.3	1'564	45.3
	Car as passenger	54	4.8	72	6.2	98	8.4	224	6.5
Public transit	Urban bus	208	18.4	257	22.2	236	20.2	701	20.3
	School/company bus	5	0.4	0	0.0	4	0.3	9	0.3
	Metro	23	2.0	52	4.5	38	3.3	113	3.3
	Suburban bus	12	1.1	8	0.7	13	1.1	33	1.0
	Train	7	0.6	6	0.5	7	0.6	20	0.6
Active modes	Walking	220	19.5	202	17.4	141	12.1	563	16.3
	Bike	47	4.2	41	3.5	26	2.2	114	3.3
Sharing modes	Bike sharing	3	0.3	4	0.3	5	0.4	12	0.3
	Car sharing	1	0.1	1	0.1	3	0.3	5	0.1
Others	Motorbike	41	3.6	28	2.4	18	1.5	87	2.5
	Taxi	2	0.2	4	0.3	3	0.3	9	0.3
	Total	1'128		1'159		1'167		3'454	

Considering the macro-trip under investigation, interviewees were asked to list all transport means they had used in the past to complete it in different occasions, as well as all those means they are considering to use in the future. The following tables present the related cross tabulation of the answers to those two questions, where a selection of the most frequently used means is listed in rows and future means are in columns. These tables consider only respondents who declared to have already carried out the selected trip chain in the past; for this reason, 167 interviews belonging to the whole sample are excluded (see Table 18) and, therefore, 3’287 interviews are retained. In particular, Table 20, Table 21, Table 23 and Table 24 show absolute and percentage values, respectively, of modal diversion patterns for the chained trip. Table 22 displays the number of respondents who reported to have used the travel mode in rows at least one time to perform the selected trip chain. Percentages reported in each cell of Table 23 and Table 24 indicate the fraction of individuals that might use the mode indicated in the column label, among all individuals having already used the mode indicated in the row label to complete at least part of the trip (i.e. values in Table 22). Less commonly selected modes to make the same chained trip in the future (such as boats crossing the Po river in Turin) were not included in columns. Furthermore, since respondents could indicate more than one past or future transport mode, row and column sums are greater than 100%.

Values in the diagonal of Table 20, Table 21, Table 23 and Table 24 are related to those interviewees who would adopt the same mode in the future. Observing the overall table, one can note that these cells have the highest values in the matrix, highlighting the strong behavioural inertia of users. Among diagonal cells, travellers by train have a low value, suggesting their dissatisfaction with such mode. On the other hand, other values show the substitution patterns across different modes for the random trip. Car as a driver has the lowest values beyond the one in the diagonal compared to other rows, thus indicating that drivers tend to stick more to their means than users of other means. On the contrary, car and bike sharers show the highest values on average, pointing out their multimodality and their attitude to share travel means, as in the case of public transport. Car passengers would ideally become drivers, but the reverse relationship is not observed. Similarly, car sharing members would use private car or urban public transport means, but the opposite relationship has not the same strength. Conversely, substitution relationships can be identified between urban public transport modes (such as urban bus and metro), and between walking and bike, to a smaller extent.

Considering columns rather than rows, private car is the most attractive mode. On the contrary, car sharing values are low if compared with those of traditional transport modes. This could be due to the fact that car sharing has been only recently introduced in Turin. Overall, car sharing seems to be a more appealing substitute of public transport, taxi and bike sharing than of car as a driver, car as a passenger, train and active means. As expected, car sharing can compete with the former modes since it can offer more flexibility rather than public transport and a privacy similar to the one of taxi, but with a lower cost. On the other hand, private car drivers exhibit a low willingness to switch to other means. Moreover, characteristics of trips performed with train and active modes are usually not suitable for car usage; in particular, train is often adopted for long inter-city trips, whereas walking and bike are used for short trips.

Table 20.Modal diversion patterns for the chained trip under analysis (absolute values) (1)

	Car as driver	Car as passenger	Motorbike	Urban bus	School/company bus	Metro
Car as driver	1’853	578	172	512	42	247
Car as passenger	527	730	83	343	17	143
Motorbike	95	56	138	50	11	20
Urban bus	492	359	100	918	37	272
School/company bus	22	12	11	26	17	14
Metro	206	146	40	240	17	319
Suburban bus	81	57	19	53	12	47
Train	45	35	10	41	5	36
Taxi	46	41	16	40	5	25
Walking	362	262	104	313	28	148
Bike	248	191	82	161	23	90
Bike sharing	30	19	27	39	7	19
Car sharing	39	29	24	36	10	28

Table 21. Modal diversion patterns for the chained trip under analysis (absolute values) (2)

	Suburban bus	Train	Taxi	Walking	Bike	Bike sharing	Car sharing
Car as driver	105	57	76	356	334	100	155
Car as passenger	57	27	49	193	154	39	70
Motorbike	9	8	15	51	61	25	24
Urban bus	72	48	68	268	201	101	108
School/company bus	7	4	9	17	15	8	7
Metro	49	34	34	105	92	51	63
Suburban bus	78	23	12	30	27	20	23
Train	21	38	10	24	9	6	7
Taxi	7	7	51	25	25	12	25
Walking	54	30	58	847	323	102	101
Bike	27	21	34	261	362	76	61
Bike sharing	9	9	8	36	39	43	22
Car sharing	13	11	17	30	31	20	39

Table 22. Total number of respondents reporting to have used the travel mode in rows for the chained trip at least one time

Mode	**N**	**Mode**	**N**
Car as driver	2’024	Train	73
Car as passenger	842	Taxi	65
Motorbike	163	Walking	941
Urban bus	1’069	Bike	455
School/company bus	36	Bike sharing	51
Metro	379	Car sharing	46

Table 23. Modal diversion patterns for the chained trip under analysis (respondent percentages) (1)

	Car as driver	Car as passenger	Motorbike	Urban bus	School/company bus	Metro
Car as driver	91.6	28.6	8.5	25.3	2.1	12.2
Car as passenger	62.6	86.7	9.9	40.7	2.0	17.0
Motorbike	58.3	34.4	84.7	30.7	6.7	12.3
Urban bus	46.0	33.6	9.4	85.9	3.5	25.4
School/company bus	61.1	33.3	30.6	72.2	47.2	38.9
Metro	54.4	38.5	10.6	63.3	4.5	84.2
Suburban bus	73.6	51.8	17.3	48.2	10.9	42.7
Train	61.6	47.9	13.7	56.2	6.8	49.3
Taxi	70.8	63.1	24.6	61.5	7.7	38.5
Walking	38.5	27.8	11.1	33.3	3.0	15.7
Bike	54.5	42.0	18.0	35.4	5.1	19.8
Bike sharing	58.8	37.3	52.9	76.5	13.7	37.3
Car sharing	84.8	63.0	52.2	78.3	21.7	60.9

Table 24. Modal diversion patterns for the chained trip under analysis (respondent percentages) (2)

	Suburban bus	Train	Taxi	Walking	Bike	Bike sharing	Car sharing
Car as driver	5.2	2.8	3.8	17.6	16.5	4.9	7.7
Car as passenger	6.8	3.2	5.8	22.9	18.3	4.6	8.3
Motorbike	5.5	4.9	9.2	31.3	37.4	15.3	14.7
Urban bus	6.7	4.5	6.4	25.1	18.8	9.4	10.1
School/company bus	19.4	11.1	25.0	47.2	41.7	22.2	19.4
Metro	12.9	9.0	9.0	27.7	24.3	13.5	16.6
Suburban bus	70.9	20.9	10.9	27.3	24.5	18.2	20.9
Train	28.8	52.1	13.7	32.9	12.3	8.2	9.6
Taxi	10.8	10.8	78.5	38.5	38.5	18.5	38.5
Walking	5.7	3.2	6.2	90.0	34.3	10.8	10.7
Bike	5.9	4.6	7.5	57.4	79.6	16.7	13.4
Bike sharing	17.6	17.6	15.7	70.6	76.5	84.3	43.1
Car sharing	28.3	23.9	37.0	65.2	67.4	43.5	84.8

In the survey, respondents had to face with Stated-preferences experiments, in which they expressed their propensity to perform the same macro-trip in the future with an alternative mode. Each interviewee had to answer to six experiments, one for each alternative, which are private car, public transport, taxi sharing, bike, bike sharing and car sharing. Respondent had to indicate their switching propensity through a 5-points ordinal scale. Table 25 shows the answers of these experiments, which are aggregated in three groups (positive, neutral and negative). In particular, rows indicate the modes currently adopted by the interviewed to complete the chained trip, and columns report the six alternative modes of the Stated-preferences experiments. Percentage values are calculated considering the total number of users currently adopting the mode reported in rows. In the original version of the survey, the modes declared by the respondents in the Travel diary section of the survey were more disaggregated, both for private (e.g. car as driver, car as passenger) and public modes (e.g. urban bus, suburban bus, metro, tram, train). However, in the six experiments, they were merged in order to match the diversification of the means proposed as alternative.

In order to get a visual representation of results in Table 25, Sankey diagrams were adopted. This type of diagram shows the flows from the elements on the left side to those on the right side, using flow bands with a width which is proportional to the flow rate. In the present case, the flows are the switching intentions from the current mode to the alternative one. Therefore, two diagrams were developed: the former considers the positive switching propensities (Figure 21), and the latter focuses on the negative answers (Figure 22).

Observing the results reported in Table 25, Figure 21 and Figure 22, one can note that car, public transport and walking are the most used transport means, while car sharing and bike sharing are not common. As highlighted by previous analysis, this reflects and confirms that both these means are not widespread among Turin residents, due to their recent introduction. Moreover, this justifies the adoption of Stated-preference experiments to understand the factors affecting the potential switching to these two modes. Positive frequencies higher than 50% are found only for the same mode already in use, suggesting that the majority of respondents chose to keep on using their means. In particular, car drivers show the strongest behavioural inertia given the low willingness to try different modes, followed by public transport users and walkers. The notable exception is the switch from bike to bike sharing, given the similarity of the two means, whereas the switch from car to car sharing is much less popular.

Comparing different columns of Table 25 allows assessing the potential attraction of different travel means towards passengers using different modes. The proportion of positive switches from private car to public transport is greater than the one describing the reverse relationship, indicating a potential attractiveness of the public transit system. Bike and bike sharing seems not very attractive to people using car and public transport. Moreover taxi sharing is even less attractive for all other means. Focusing on car sharing, overall, it is much less attractive than public transport and car. Specifically, the relationship with both private car and public transport is ambiguous, since positive and negative intentions are reported for both the two modes. However, it seems more attractive for public transport users rather than for car drivers ($\chi^2 = 32.141$, p-value < 0.01). Furthermore, positive switches are reported also from bike, but not from walking. The analysis of the attractiveness of each transport modes is important to outline how the distribution of the actual travel demand could potentially change considering the introduction of an innovative transport mode, such as car sharing.

In conclusion, car drivers show the strongest behavioural inertia to change their mode. Car sharing attractiveness is low if compared with those of traditional transport modes. This could be due to the fact that car sharing has been only recently introduced in Turin. Overall, car sharing seems to be a potential substitute of private car, public transport and taxi rather than train and walking. These preliminary results can give an overview of the substitution and complementarity patterns among different means, but it is important to deepen our understanding of the underlying factors that can explain such trends.

Table 25. Switching intentions from the current mode (in rows) to the alternative one (in columns)

Switching from…	intention	To… Car N	%	Public transport N	%	Taxi sharing N	%	Bike N	%	Bike sharing N	%	Car sharing N	%
Car	**Yes**	1'256	67.0	839	44.7	149	7.9	214	11.4	200	10.7	464	24.7
	Neutral	260	13.9	332	17.7	178	9.5	162	8.6	150	8.0	248	13.2
N = 1'875	**No**	359	19.1	704	37.5	1'548	82.6	1'499	79.9	1'525	81.3	1'163	62.0
Public	**Yes**	227	25.9	525	59.9	79	9.0	98	11.2	100	11.4	133	15.2
transport	**Neutral**	210	24.0	146	16.7	77	8.8	85	9.7	61	7.0	119	13.6
N = 876	**No**	439	50.1	205	23.4	720	82.2	693	79.1	715	81.6	624	71.2
Taxi	**Yes**	1	11.1	1	11.1	1	11.1	1	11.1	1	11.1	4	44.4
	Neutral	2	22.2	1	11.1	1	11.1	2	22.2	3	33.3	1	11.1
N = 9	**No**	6	66.7	7	77.8	7	77.8	6	66.7	5	55.6	4	44.4
Walking	**Yes**	66	11.7	153	27.2	22	3.9	155	27.5	122	21.7	36	6.4
	Neutral	72	12.8	92	16.3	42	7.5	75	13.3	64	11.4	45	8.0
N = 563	**No**	425	75.5	318	56.5	499	88.6	333	59.1	377	67.0	482	85.6
Bike	**Yes**	31	27.2	52	45.6	12	10.5	90	78.9	71	62.3	27	23.7
	Neutral	19	16.7	19	16.7	9	7.9	10	8.8	19	16.7	11	9.6
N = 114	**No**	64	56.1	43	37.7	93	81.6	14	12.3	24	21.1	76	66.7
Bike	**Yes**	4	33.3	5	41.7	1	8.3	7	58.3	7	58.3	7	58.3
sharing	**Neutral**	5	41.7	5	41.7	2	16.7	5	41.7	3	25.0	2	16.7
N = 12	**No**	3	25.0	2	16.7	9	75.0	0	0.0	2	16.7	3	25.0
Car	**Yes**	2	40.0	4	80.0	1	20.0	3	60.0	4	80.0	2	40.0
sharing	**Neutral**	1	20.0	0	0.0	1	20.0	1	20.0	0	0.0	1	20.0
N = 5	**No**	2	40.0	1	20.0	3	60.0	1	20.0	1	20.0	2	40.0

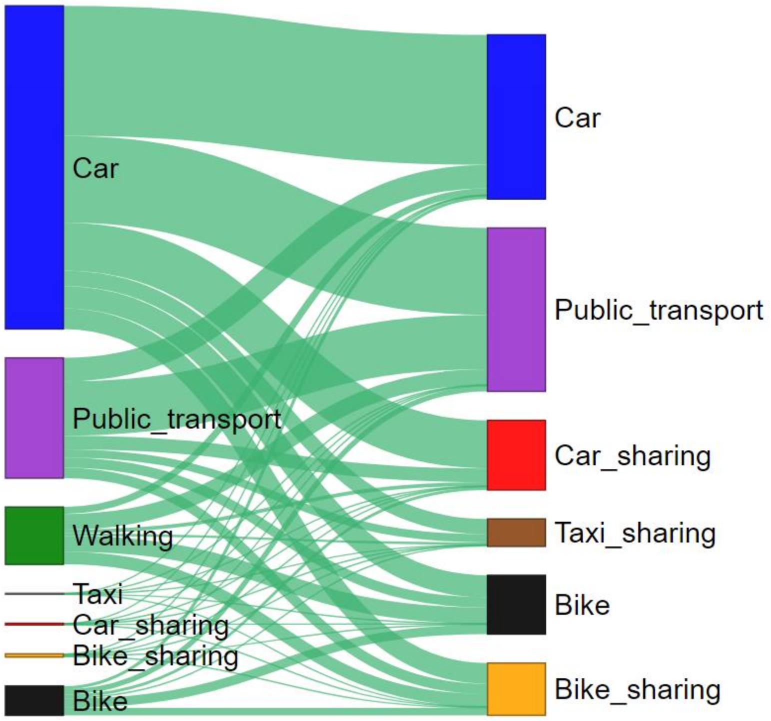

Figure 21. Sankey diagram for positive switches from the current mode (left side) to the alternative one (right side)

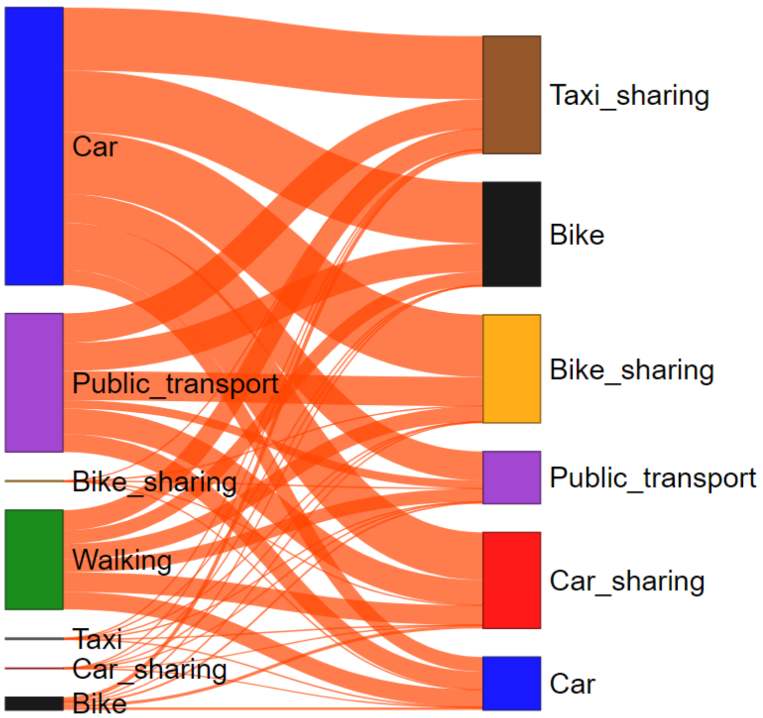

Figure 22. Sankey diagram for negative switches from the current mode (left side) to the alternative one (right side)

Chapter 5

Models

In this chapter, data collected through the travel survey were used as input to different models, each of which had a specific aim. Specifically, in the first model, a logistic regression was adopted to identify variables affecting the decision to join the car sharing service. The same technique was implemented for the second model, the aim of which was to understand how the characteristics of potential users of car sharing interact with both trip attributes and past and future multimodality behaviours, in order to adopt car sharing to perform the macro-trip under analysis in the future. Moreover, the third group of models had multiple aims. The first one was to define factors that influence the decision to switch from the travel mode effectively adopted to carry out the macro-trip towards car sharing. The second one was to analyse the relationship of car sharing with existing travel means (in particular, private car, public transport, bike and walking), in order to identify potential relationship of substitution or complementarity. The third aim was to define the best domain (or ambit of use) of each travel modes, i.e. the characteristics of the trips which are more likely to be performed with each mode. In order to reach these targets, three methods were applied: logit models based on Random Utility Maximization theory, Decision Trees and a visual approach. The obtained results were compared to assess the potentiality and limitations of each technique.

The first model was named “car sharing membership model” because of its aim; the second model was labelled as “propensity model”, whereas the third groups of models were defined as “choice” or “switching models”. The rationale behind the two last names was based on the difference between the two models. Indeed, through the propensity model, generic attitudes of respondents towards the potential use of car sharing were analysed, without considering the characteristics of possible future trips which they might carry out on that travel mode, but rather focusing on multimodality behaviours. It is worth noting that the reported propensities might not come true, since they were evaluated by generic preferences. On the other hand, choice models were adopted to test the effective decision to use car sharing to perform a specific real trip, thereby forecasting which trips might be diverted to car sharing. In particular, Stated-preferences experiments, which were used to calibrate these models, considered changes in the Level Of Service of car sharing, in order to generate realistic characteristics of travelling on this mode. For these reasons, the second and third models can be considered as complementary, contributing to generate a framework for the analysis of potential car sharing adoption.

Each of the following subsections contains the specification and calibration framework of each model, in addition to a discussion of modelling results. It is worth noting that independent variables adopted to calibrate the models include socio-economic and contextual factors of interviews and their households, as well as travel habits of individuals and characteristics of performed and potential trips. However, attitudinal and affective factors were not considered, even if they can play a significant role in the choice to adopt car sharing (Efthymiou et al., 2013; Kim et al., 2017b; Ramos et al., 2020), since questions in the travel survey do not allow to an exhaustive definition of such variables.

5.1. Car sharing membership

In order to analyse which factors affect the choice to become a member of a car sharing system in Turin, a logistic regression models was adopted. In particular, the model predicts the probability for a respondent to own a car sharing subscription. Since the corresponding variable used as outcome is binary, a binomial logit model was implemented. Independent variables were first selected according to literature review; then, non-significant variables were removed both manually and using an automated stepwise procedure, obtaining different models which were compared; after that, the best model was retained. Exogenous variables inserted in the final model specification are shown in Table 26; as one can note, both individual and household levels are considered. In order to avoid collinearity problems, correlations among these variables were calculated, considering Pearson coefficients when both variables were metric, Phi coefficients for correlations between two dichotomous variables, and point-biserial correlations when one variable was metric and the other dichotomous. The entire procedure was carried out using R software (R Core Team, 2019). Moreover, since only drivers are obviously allowed to use car sharing, only 2’957 respondents owing a driving license were retained.

Table 26. Exogenous variables for the car sharing membership model

	Description	**Type**	**Level**
AGE	Age	Metric	Individual
D_MPHD	Master's degree or Ph.D. *(ref. High school graduated)*	Dummy	Individual
D_NHS	Not high school graduated *(ref. High school graduated)*	Dummy	Individual
D_RET	Retired *(ref. Working out of home)*	Dummy	Individual
D_STN	Student *(ref. Working out of home)*	Dummy	Individual
D_UNE	Unemployed *(ref. Working out of home)*	Dummy	Individual
D_WAH	Working at home *(ref. Working out of home)*	Dummy	Individual
HH_cars	Number of cars	Metric	Household
HH_driv	Number of driving licenced	Metric	Household
HH_inc	Income [1000€]	Metric	Household
HH_memb	Number of members	Metric	Household
HH_mtb	Number of motorbike	Metric	Household
PARK_HOME	Private parking near home	Dummy	Individual
PT_PASS	Public transit pass	Dummy	Individual

Estimation results are presented in Table 27. Like in previous works, age has a negative impact, however it is not so significant compared with other variables in the model (Odds Ratio). Concerning the occupational status of the respondent, students (D_STN) and unemployed people (D_UNE) are less willing to become car sharing members if compared with employed people working out of home. Furthermore, like in other studies, car sharing members tend to have a high educational level (D_MPHD is positive). Moreover, as obtained by other authors (Clewlow, 2016; Dias et al., 2017), if the household income increases, the probability to buy a subscription grows (HH_inc is positive). A similar effect is noted for the number of household members owning a driving licence (HH_driv is positive), since, with an higher competition to use the household cars, it is more likely that someone decides to adopt car sharing. On the contrary, the effect of the number of household members is negative (HH_memb), as found by other authors (Becker et al., 2017c). Like in previous studies, car availability plays a significant and negative role. In particular, the number of vehicles owned has a negative effect (HH_cars), since users tend to use available household cars rather than car sharing, confirming the previous consideration about driving licenced members. In addition, the presence of private parking near home is an incentive to drive private vehicles (PARK_HOME is negative), lowering the probability to use car sharing. Car sharing members also tend to own a public transport pass (PT_PASS), suggesting that car sharing is considered and used as a complementary mode to public transport. In conclusion, car sharing is used by young employed persons with a high educational level and who live in low-size households, with few private cars, many licenced drivers and a high income.

Table 27. Car sharing membership model

	Estimate	Std. Error	z value	Odd Ratio	p value	
Intercept	-0.688	0.493	-1.395	0.502	0.163	
AGE	-0.037	0.010	-3.810	0.964	0.000	***
D_WAH	-0.744	0.614	-1.212	0.475	0.225	
D_STN	-0.942	0.362	-2.603	0.390	0.009	**
D_RET	-0.224	0.503	-0.444	0.800	0.657	
D_UNE	-1.548	0.503	-3.076	0.213	0.002	**
D_NHS	-0.028	0.423	-0.066	0.972	0.947	
D_MPHD	0.547	0.195	2.807	1.728	0.005	**
PT_PASS	0.703	0.204	3.449	2.019	0.001	***
PARK_HOME	-1.699	0.199	-8.523	0.183	0.000	***
HH_memb	-0.305	0.137	-2.231	0.737	0.026	*
HH_driv	0.464	0.181	2.567	1.590	0.010	*
HH_cars	-0.445	0.178	-2.507	0.641	0.012	*
HH_mtb	0.446	0.181	2.469	1.562	0.014	*
HH_inc	0.228	0.070	3.237	1.256	0.001	**

Significance codes: *** p< 0.001; ** p< 0.01; * p< 0.05; † p<0.10

Statistics

N = 2’957	
Null deviance	1’133.34
Residual deviance	945.16
AIC (Aikake Criterion)	975.16
Null Log-likelihood	-566.67
Final Log-likelihood	-472.58
Cragg and Uhler's pseudo R2	0.19
McFadden's pseudo R2	0.17
Maximum likelihood pseudo R2	0.06

In this model, positive correlations were obtained between the number of members (HH_memb) and the number of licenced drivers (HH_driv) (Pearson $\rho = 0.72$, *p-value* < 0.001), however, the two parameters have opposite effects on the dependent variables of the model. Similarly, a high correlation coefficient was found between the age (AGE) and the dummy variable related to retired people (D_RET) (Point-biserial $r_{pb} = 0.70$, *p-value* < 0.001), as expected, since old people tend to be retired; nevertheless, D_RET was not retained in the final model specification, therefore these correlated values do not affect the model validity.

5.2. Car sharing propensity

In order to complement the results of the first model and, in particular, to understand how the characteristics of potential users of car sharing interact with both trip attributes and past and future multimodality behaviours, an additional model was developed presenting a trip-level analysis. The model estimates the probability to adopt car sharing to perform the macro-trip under analysis in the future. The dependent variable of the model was derived from a question where a list of travel modes was shown to the respondent, who had to state whether she is likely to use (or not) each them, to carry out the macro-trip in the future (the specific question was labelled as "FUT_MODO", in Section D of the travel survey; the reader is referred to the corresponding question in Appendix A for further details). In particular, car sharing was one of the proposed future potential transport means; specifically, the exogenous variable is equal to 1 if the interviewed indicates that she is likely to adopt car sharing in the future, otherwise the variable is equal to 0. Therefore, like for the car sharing membership model, a binary logistic regression technique was implemented. Table 28 reports the exogenous variables of the definitive specification of the model, which were selected both manually and using an automated stepwise procedure. Exogenous variables are categorised in three different levels: individual, household and macro-trip level. Moreover, correlation coefficients were evaluated in order to avoid collinearity. In particular, Pearson coefficients were used when both variables were metric, Phi coefficients for correlations between two dichotomous variables, and point-biserial correlations when one variable was metric and the other dichotomous. The whole procedure was carried out using R software (R Core Team, 2019). Since also past travel choices are considered as exogenous variables in the model, only respondents who declared to have already carried out the selected trip chain in the past were retained, thus obtaining 3'287 interviews.

Table 28. Exogenous variables for the car sharing future use model

	Description	Type	Level
AGE	Age	Metric	Individual
CS_pass	Car sharing subscription	Dummy	Individual
F_bshar	Frequency of use of bike sharing [times/week]	Metric	Individual
F_cshar	Frequency of use of car sharing [times/week]	Metric	Individual
F_scb	Frequency of use of school bus sharing [times/week]	Metric	Individual
F_ubus	Frequency of use of urban bus [times/week]	Metric	Individual
FUT_bshar	Willing to use bike sharing in the future for this trip	Dummy	Macro-trip
FUT_cardriv	Willing to use car as driver in the future for this trip	Dummy	Macro-trip
FUT_carpass	Willing to use car as passenger in the future for this trip	Dummy	Macro-trip
FUT_mtb	Willing to use motorbike in the future for this trip	Dummy	Macro-trip
FUT_scb	Willing to use school bus in the future for this trip	Dummy	Macro-trip
FUT_subus	Willing to use suburban bus in the future for this trip	Dummy	Macro-trip
FUT_taxi	Willing to use taxi in the future for this trip	Dummy	Macro-trip
GOO_DIST	Distance [kilometres]	Metric	Macro-trip
GOO_TIME	Time [minutes]	Metric	Macro-trip
HH_cars	Number of cars	Metric	Household
HH_work	Number of employees	Metric	Household
INTERV_CAWI	CAWI interview	Dummy	Individual
ORIG_TO	Origin inside Turin	Dummy	Macro-trip

PAST_cardriv	Used car as a driver in the past for this trip	Dummy	Macro-trip
PAST_cshar	Used car sharing in the past for this trip	Dummy	Macro-trip
PAST_metro	Used metro in the past for this trip	Dummy	Macro-trip
PAST_scb	Used school/company bus in the past for this trip	Dummy	Macro-trip
PAST_train	Used train in the past for this trip	Dummy	Macro-trip
WORKDAY	Working day	Dummy	Macro-trip

Results of model estimation are shown in Table 29. As regards socio-economic variables both at individual and household level, consistently with the previous model and with other studies, the age of the respondent (AGE) and the number of cars owned (HH_cars) have a negative effect. On the contrary, if the number of employees in the household (HH_work) increases then the probability to use car sharing grows.

People currently using car sharing seem satisfied with the service and are likely to use it in the future, since coefficients related to the car sharing subscription (CS_pass) and the frequency of past use in general (F_cshar) and for the specific trip (PAST_cshar) use are all positive and with high odds ratios. The propensity increases as the frequency of trips on urban bus increases (F_ubus), this seems to point more to a complementarity than to a substitution effect between the two means, since F_ubus is related to all trips while the use of the bus for the trip under investigation was not found significant. Along the same lines of interpretation, both F_scb and PAST_scb are both negative, suggesting that school and company buses serve trips that are not well suit to car sharing. Similarly, potential users are going to use car sharing less on a working day (WORKDAY is negative). Jointly considered, these two aspects show that car sharing is not likely to be used for systematic trips, like school and work. The frequency of use of bike sharing has a negative effect (F_bshar) while the intended future use of this means for the specific trip (FUT_bshar) is positively correlated: there is thus a clear complementarity between the two modes. The same can be said in particular for taxis (FUT_taxi coefficient is positive while the actual use of this means was not found significant, possibly due to its low level of use). Finally, car sharing seems to be attractive for long-duration (GOO_TIME is positive) and short-distance (GOO_DIST is negative) trips, which are characteristics of urban trips in congested streets.

In order to clarify the relationship of car sharing with other transport means, the effect of variables "PAST_*" on the outcome can be analysed. In particular, negative signs of PAST_scb and PAST_train indicate that car sharing cannot substitute these modes; the first one is used for systematic trips (as described above), while, the latter is used for long distance (in fact GOO_DIST has a negative sign). On the contrary, PAST_cardriv and PAST_metro have both a positive effect, suggesting that car sharing can substitute these two modes, which are characteristic of urban trips. Moreover, both past use of car as driver and metro have an impact greater than school/company bus and train, since their odd ratios are higher, indicating that car sharing will be a real future alternative of these means. On a more general note, variables related to the future use of other transport modes are all positive; this shows that, like previous works, multimodality positively affects the propensity to use car sharing (Diana, 2010). Concerning the spatial characteristics of the trip, only ORIG_TO is significant, independently on the trip destination, possibly pointing to a not completely rational behaviour, in which the availability of car sharing near the trip departure point is more affecting travel choices than the possibility of dropping the car within the service operational area. Lastly, respondents interviewed with CAWI are more likely to use car sharing in the future, since car sharing users are usually familiar with smartphone and web applications.

Table 29. Car sharing future use model

	Estimate	Std. Error	z value	Odd Ratio	p value	
Intercept	-4.948	0.703	-7.038	0.007	0.000	***
AGE	-0.016	0.008	-1.897	0.984	0.058	†
HH_work	0.346	0.152	2.276	1.413	0.023	*
HH_cars	-0.372	0.169	-2.201	0.689	0.028	*
F_bshar	-0.339	0.157	-2.163	0.713	0.031	*
F_cshar	0.881	0.155	5.671	2.415	0.000	***
F_scb	-0.482	0.158	-3.046	0.618	0.002	**
F_ubus	0.184	0.072	2.558	1.202	0.011	*
CS_pass	1.251	0.298	4.199	3.493	0.000	***
WORKDAY	-0.880	0.372	-2.365	0.415	0.018	*
GOO_TIME	0.044	0.018	2.485	1.045	0.013	*
GOO_DIST	-0.044	0.025	-1.769	0.957	0.077	†
ORIG_TO	-0.546	0.247	-2.212	0.579	0.027	*
PAST_cardriv	0.493	0.286	1.721	1.637	0.085	†
PAST_cshar	2.446	0.587	4.166	11.539	0.000	***
PAST_scb	-1.850	0.857	-2.158	0.157	0.031	*
PAST_metro	0.564	0.259	2.181	1.758	0.029	*
PAST_train	-1.847	0.656	-2.816	0.158	0.005	**
FUT_bshar	1.214	0.277	4.389	3.368	0.000	***
FUT_mtb	0.749	0.248	3.015	2.115	0.003	**
FUT_cardriv	0.827	0.318	2.602	2.286	0.009	**
FUT_carpass	0.746	0.215	3.469	2.109	0.001	***
FUT_taxi	1.242	0.318	3.906	3.462	0.000	***
FUT_scb	1.099	0.448	2.455	3.001	0.014	*
FUT_subus	1.040	0.303	3.430	2.828	0.001	***
INTERV_CAWI	2.450	0.270	9.065	11.587	0.000	***

Significance codes: *** p< 0.001; ** p< 0.01; * p< 0.05; † p<0.10

Statistics

N = 3’287	
Null deviance	1’556.18
Residual deviance	742.99
AIC (Aikake Criterion)	794.99
Null Log-likelihood	-778.09
Final Log-likelihood	-371.49
Cragg and Uhler's pseudo R2	0.58
McFadden's pseudo R2	0.52
Maximum likelihood pseudo R2	0.22

Analysing correlations among exogenous variables of the second model, a high value was obtained between the distance (GOO_DIST) and the duration (GOO_TIME) of the macro-trip (Pearson $\rho = 0.83$, *p-value* < 0.001), however even if the correlation is positive, the two parameters have opposite effects on the dependent variables of the model. A negative correlation (Pearson $\rho = 0.61$, *p-value* < 0.001) was obtained between the age of the respondents (AGE) and the number of employees in the household (HH_work), indicating that old people might live in households with retired people. A positive correlation (Index $\phi = 0.79$, *p-value* < 0.001) was found between past (PAST_csrdriv) and future use of car as driver (FUT_cardriv), indicating that who adopted a car for the macro-trip is likely to use it in the future.

5.3. Switching intentions towards car sharing

5.3.1. Introduction

In order to predict potential trips carried out on car sharing and to analyse which factors might affect the decision to switch to this mode, three kinds of approaches were developed. The first method is a traditional econometric model, namely a logit model; the second one is a data mining technique, specifically a Decision Tree model; the third one is a descriptive visual approach. The three proposed approaches differ in their basic assumptions; in particular, logit model is based on the Random Utility Maximization theory, Decision Tree extracts significant patterns directly from the data, and the visual approach is a descriptive method which does not require any statistical assumption. Therefore, each approach faces the problem from a different perspective, whereby many results were obtained enriching the analysis about switching intentions towards car sharing.

Since one of the aims of the present work is to understand the relationship of car sharing with traditional travel means, the analysis was diversified according to the mode currently adopted by users, in order to consider the effects of the original means. Specifically, the users' intentions to perform the reported macro-trip on car sharing in the future are modelled through two groups of models. The first group carried out this analysis considering the currently adopted mode as an exogenous variable, thus all the observations were used to calibrate this set of models. The second group divide the sample into subsets according to the actual travel mode, which was used to perform the macro-trip. In this way, unlike previous works, variables affecting the switching intentions are mode specific, leading to a deeper understanding of the relationship between each traditional means and car sharing. This procedure was followed for both logit models and Decision Trees.

Both the models were calibrated and validated using the same dataset, in order to compare their results in terms of variables effect and prediction performances. In particular, since the aim is to analyse the switch towards car sharing, Stated-preferences experiments were considered, and only experiments with car sharing as alternative choice were retained. The specific question was labelled as "SWITCH_CSHAR" in Section E of the travel survey. A brief description of that question was summarized in the introduction of Appendix A, moreover Figure 46 shows a screen snapshot of its structure. Furthermore, the reported travel modes were aggregated as follows. Car mode includes car as driver and car as passenger, whereas public transport mode includes urban bus, suburban bus, metro, train and school/company bus. Therefore, four base modes were selected: car, public transport, bike and walking. Moreover, even if answers are expressed through an ordinal scale, the results of the experiments were aggregated into two groups, thus obtaining a binary output. In particular, answers with "I am not at all inclined to use the switching mode" and "I am not very inclined to use the switching mode" were grouped as the choice to keep on using the current travel mode for the macro-trip. Whereas answers with "I am slightly inclined to use the switching mode" and "I am strongly inclined to use the switching mode" were aggregated as the decision to switch to car sharing. In this way, both logit models and Decision Trees share the same dependent variable. Furthermore, neutral answers were discarded, and not added to negative shift answers, in order to avoid a highly unbalanced sample of answers.

It is worth noting that, in general, a neutral answer can have two different meanings (Cantillo et al., 2010). The former can indicate that the respondent has an utility that none of the proposed alternatives can provide, whereas in the second case, the individual is indifferent respect to the alternatives, since the perceived utilities given by the choice options are approximately equal (Bahamonde-Birke et al., 2017; Hess et al., 2014). In the present survey, the interpretation of the neutral answers might be closer to the second option.

Discarding neutral responses is an approach that was adopted in few previous works (Björklund and Swärdh, 2017; Carrel and Walker, 2017; Nordland et al., 2013) with different purposes: for instance, in order to reduce model complexity, by converting results from a Likert scale to binary response (Carrel and Walker, 2017), or since neutral answers had no significance for the scope of the analysis (Nordland et al., 2013). However this approach leads to a loss of information, since the sample size is lowered and the removed observations are not analysed (Blanchi et al., 1998; Ortuzar and Willumsen, 2011; Ortúzar and Garrido, 1994a, 1994b). In addition many authors compared results of logit models, which were calibrated neglecting neutral answers, with alternative models, which considers even these responses, observing a decrease of performance indicators, and higher estimation and prediction errors when the first approach was adopted (Antoniou et al., 2007; Bahamonde-Birke et al., 2017; Blanchi et al., 1998; Cantillo et al., 2010; Hess et al., 2014; Ortúzar and Garrido, 1994b). In order to overcome this issue, several methods were proposed. In binary choice tasks, observations with neutral answers can be aggregated to those of an alternative (Peeta et al., 2000; Peeta and Yu, 2002); however, this might lead to potential biased estimation results (Fenichel et al., 2009), since different degrees of preferences are considered (Ortúzar and Garrido, 1994b). Alternatively, ordered logit or probit models were adopted, allowing to explicitly account the neutral responses within an ordered scale of answers (Antoniou et al., 2007; Beck et al., 2017; Blanchi et al., 1998; Ortúzar and Garrido, 1994b). Furthermore, other models were developed in order to consider the indifference option in Stated-preference experiments, with more than two alternatives (Bahamonde-Birke et al., 2017; Cantillo et al., 2010). Besides models based on Random Utility Maximization theory, methods based on Random Regret Minimization framework were successfully used to consider the opt-out option (Hess et al., 2014; Jang et al., 2018).

Since one of the two alternatives is “stay with the current travel mode”, the neutral answers could have been aggregated to the status quo alternative, however this would have generated a highly unbalanced dataset, with loss of prediction performances for the alternative choice. Moreover, since one of the aims of this thesis is to test different approaches, neutral answers were discarded and the remaining ones were aggregated into two alternatives, in order to use the same exogenous variables for all the adopted methods, even if this methodology is not suggested (Ortúzar and Garrido, 1994b).

In order to calibrate and validate both logit models and Decision Trees, each input dataset was randomly divided into a training dataset and a test dataset (Ortuzar and Willumsen, 2011). In particular, a stratified random sampling technique was adopted, which ensures that the distribution of dependent variables is the same in the two subsamples. Thus, 70% of the overall sample was selected to calibrate the models and the remaining 30% was considered to validate them. The same subsets were adopted for both types of models, in order to compare the obtained results. The number of observations in each subsample is shown in Table 30, where different groups of models are reported in columns. Moreover, predicted performances were compared to analyse the predictive capability and transferability power of the two models (Lindner et al., 2017; Tang et al., 2015; Xie et al., 2007).

Table 30. Number of Stated-preferences answers in the calibration and validation subsamples for different models (in columns)

	Switch	**All**	**Car**	**Public transport**	**Bike**	**Walking**
Calibration	Positive	442	303	93	20	26
	Negative	1’608	782	437	52	337
	Total	2’050	1’085	530	72	363
Validation	Positive	192	129	40	12	11
	Negative	685	335	187	19	144
	Total	877	464	227	31	155
Total		2’927	1’549	757	103	518

On the other hand, the aim of the visual approach was to identify the best ambit of use of each travel mode, including car sharing. In order to reach this aim, the results of the switching decisions were compared for different travel modes. In particular, through this method trip attributes in both Revealed-preferences parts and Stated-preferences experiments were considered.

In the next three sections, the three approaches are described and related estimation results are presented. After that, in the last section, performances of logit models and Decision Trees are analysed and outcomes of all the three methods are summarized.

5.3.2. Random Utility Models

Introduction

The most common theoretical framework to model discrete mode choice is based on Random Utility Maximization Theory (Domencich and McFadden, 1975; Ortuzar and Willumsen, 2011). According to this approach, each generic individual q, who has to choose among j available alternatives, and who belongs to a homogeneous populations, has perfect information about the alternatives and acts in a rational way, i.e. she always choses the alternative which maximizes her personal utility (Ortuzar and Willumsen, 2011). Since the researcher does not have complete and perfect knowledge about the factors that induce the individual's choice, the utility associated with a generic alternative j is defined as:

$$U_{jq} = V_{jq} + \varepsilon_{jq}$$

Following this formulation, the utility U_{jq} is divided into two parts: the former (V_{jq}) is known by the modeller up to some parameters, whereas the latter (ε_{jq}) is unknown and, therefore, it is treated as random (Train, 2003). The first part is estimated as:

$$V_{jq} = \sum_{k} \theta_{kj} x_{jkq}$$

Where x_{jkq} represents the level k of a generic attribute x of alternative j and individual q, and θ_{kj} is the related coefficient. As regards the second part of the utility function, according to the logit approach, ε_{jq} is distributed independently, identically (IID) extreme value, namely Gumbel and type I extreme value (Train, 2003). Therefore, let $A(q)$ be the set of available alternatives of an individual q, a generic alterative A_j is chosen by q if:

$$U_{jq} \geq U_{iq}, \forall A_i \in A(q)$$

Consequently, the probability to choose A_j is defined as:

$$P_{jq} = Prob\left(V_{jq} + \varepsilon_{jq} \geq V_{iq} + \varepsilon_{iq}, \forall i \neq j\right) = Prob(\varepsilon_{iq} \leq \varepsilon_{jq} + \left(V_{jq} - V_{iq}\right), \forall i \neq j)$$

After some algebraic manipulations which apply the previous hypothesis on ε_{jq} (Ortuzar and Willumsen, 2011; Train, 2003), the probability of a traveller q choosing the mode i for a trips is given by:

$$P_{iq} = \frac{e^{V_{iq}}}{\sum_{A_i \in A(q)} e^{V_{jq}}}$$

This formula is a closed form and readily interpretable (Train, 2003), furthermore the estimation of parameters can be carried out by applying the Maximum Likelihood approach (McFadden, 1974; Train, 2003).

In this section, logit models were estimated to analyse the probability to choose between two alternative modes to perform the selected macro-trip in the future; the former alternative is the base mode (i.e. the one reported by respondents), whereas the second alternative is car sharing. Consequently, the same task can be viewed as the choice between keeping the already adopted mode or switching to car sharing. According to this perspective, the calibration of binomial logit models allowed to identify significant variables affecting the switching intention towards car sharing. In particular, five logit models were estimated, following the approach described in Figure 23. The first one considers all the observation, whereas each of the other four models was calibrated considering only trips carried out by one mode adopted by respondents (private car, public transport, bike and walking). The estimation procedure was carried out using Biogeme software (Bierlaire, 2018).

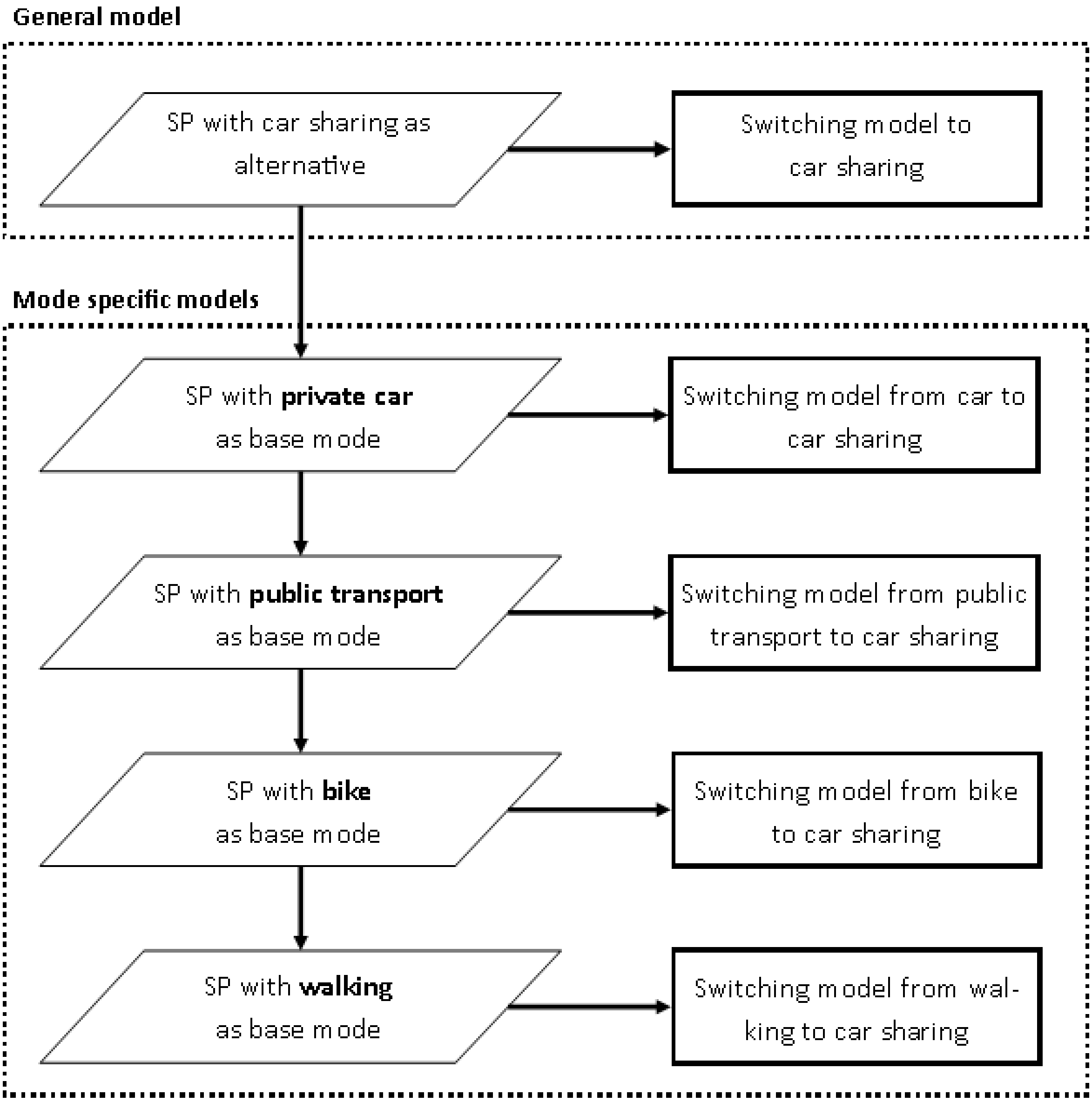

Figure 23. Flow chart for the calibrated switching models

Switching model from all modes towards car sharing

In this section, the results of the model predicting the probability to switch to car sharing are presented. In this case, all the selected interviews were considered to calibrate the model, considering the currently adopted modes as exogenous variables. Table 31 shows a description of the exogenous variables inserted in the model specification, which are related to individuals, households and macro-trip attributes.

Table 31. Exogenous variables for the car sharing switching model

	Description	Type	Level
Intercept_CS	Intercept for the car sharing alternative		
AGE	Age	Metric	Individual
BASE_cost	Cost of the base mode [€]	Metric	Macro-trip
BASE_dur	Trip duration of the base mode [min]	Metric	Macro-trip
BASE_walk_dist	Walking distance to reach the base mode [km]	Metric	Macro-trip
CS_cost	Cost of car sharing trip [€]	Metric	Macro-trip
CS_pass	Car sharing subscription	Metric	Individual
CS_walk_dist	Walking distance to reach the shared car [km]	Metric	Macro-trip
D_MPHD	Master's degree or Ph.D. *(ref. Not High school graduated)*	Dummy	Individual
D_PT	Public transport currently adopted *(ref. Private car)*	Dummy	Macro-trip
D_RET	Retired *(ref. Working out of home)*	Dummy	Individual
D_WALK	Walking mode currently used *(ref. Private car)*	Dummy	Macro-trip
F_bike	Frequency of use of bike [times/week]	Metric	Individual
F_car	Frequency of use of car [times/week]	Metric	Individual
HH_cars	Number of cars	Metric	Household
HH_driv	Number of driving licenced	Metric	Household
HH_inc	Income [1000€]	Metric	Household
HH_memb	Number of members	Metric	Household

Table 32 reports the estimation results of the car sharing switching model. Compared with the base mode, the intercept related to car sharing alternative is negative (Intercept_CS), suggesting that users tend not to give up their currently adopted mode, highlighting their behavioural inertia. As expected, the coefficients of cost of both car sharing (CS_cost) and the base mode (BASE_cost) are negative. Observing coefficients of attributes of the macro-trip, one can note that car sharing switching intentions are affected only by cost, whereas the choice of the base alternative depends also on trip duration (BASE_dur). A possible explanation is that car sharing cost is already based on duration, on the contrary BASE_dur includes also waiting time at the transit stop, in case of public transport means, which is particularly perceived by travellers. As regards the currently adopted mode, coefficients related to public transport (D_PT) and walking (D_WALK) are both negative and significant, taking private car as the reference category. This indicates that these two modes have a negative effect on car sharing switching probability, suggesting that they are less likely to be substituted by car sharing, rather than private car.

Unlike models described in the previous sections, age of respondent has a positive effect (AGE), however, being a retired people has a negative effect (D_RET), respect to working out of home.

Therefore, the age coefficient might be positive since interviewees who reported to switch were adults working out of home, but not so old to be retired. This result was indicated by statistical analysis in (Section 4.4), where the percentages of car sharing members working out of home and those retired are respectively higher and lower, respect to non-members. Like previous works, a high educational level has a positive effect on the switching choice (D_MPHD), as suggested by the greater percentage of graduated persons among car sharing members, rather than non members obtained in (Section 4.4). Moreover, coefficients related to weekly frequencies of both bike (F_bike) and private car (F_car) are positive, highlighting that car sharing potential users tend to have multimodal travel habits, as confirmed by the high percentages of use of these travel means of descriptive statistics in (Section 4.4). Furthermore, owning a car sharing subscription is a key factor for the shift, indicating that car sharing members are satisfied with the service and are likely to use it in the future. Concerning the household level, like in the previous models and statistical analysis in (Section 4.4), living in small households (HH_memb) with a high income (HH_inc) and few private cars (HH_cars) has a positive effect on potential car sharing use.

Table 32. Car sharing switching model

	Estimate	Std. Error	t test	p value	
Intercept_CS	-2.120	0.387	-5.49	0.000	***
CS_cost	-0.462	0.093	-4.99	0.000	***
CS_walk_dist	-0.076	0.000	-1.18	0.237	
BASE_cost	-0.269	0.086	-3.12	0.002	**
BASE_dur	-0.007	0.003	-2.19	0.028	*
BASE_walk_dist	-0.217	0.000	-1.10	0.273	
D_PT	-0.443	0.196	-2.26	0.024	*
D_WALK	-1.530	0.237	-6.48	0.000	***
AGE	0.534	0.187	2.86	0.004	**
D_RET	-0.699	0.195	-3.59	0.000	***
D_MPHD	0.362	0.135	2.68	0.007	**
CS_pass	1.450	0.326	4.46	0.000	***
F_bike	0.195	0.060	3.25	0.001	**
F_car	0.138	0.053	2.62	0.009	**
HH_memb	-0.278	0.082	-3.38	0.001	***
HH_cars	-0.637	0.120	-5.31	0.000	***
HH_driv	-2.120	0.387	-5.49	0.000	***
HH_inc	0.139	0.058	2.40	0.016	*

Significance codes: *** $p< 0.001$; ** $p< 0.01$; * $p< 0.05$; † $p<0.10$

Statistics

N = 2’050	
Init log likelihood	-4’054.86
Final log likelihood	-1’137.91
Likelihood ratio test for the init. Model	5’833.91
Rho-square for the init. Model	0.72
Rho-square-bar for the init. Model	0.72
Akaike Information Criterion	2’311.82
Bayesian Information Criterion	2’415.11

Switching model from private car towards car sharing

In order to evaluate variables affecting the switching intention from private car to car sharing, a specific model was calibrated considering only respondents who reported private car as the currently adopted mode for the macro-trip. In this way, 1’085 interviews were retained. Table 33 shows the selected exogenous variables, whereas Table 34 presents estimation results.

Table 33. Exogenous variables for the switching model from car to car sharing

	Description	Type	Level
Intercept_CS	Intercept for the car sharing alternative		
AGE	Age	Metric	Individual
BASE_cost	Cost of the base alternative [€]	Metric	Macro-trip
CS_cost	Cost of car sharing trip [€]	Metric	Macro-trip
CS_pass	Car sharing subscription	Metric	Individual
D_MPHD	Master's degree or Ph.D. *(ref. Not High school graduated)*	Dummy	Individual
D_RET	Retired *(ref. Working out of home)*	Dummy	Individual
DEST_TO	Trip destination within Turin Municipality	Dummy	Macro-trip
F_bike	Frequency of use of bike [times/week]	Metric	Individual
HH_inc	Income [1000€]	Metric	Household
LTZ	Trip destination within a limited traffic zone	Dummy	Macro-trip
NOWORKDAY	Non-working day	Dummy	Macro-trip
ORIG_TO	Trip origin within Turin Municipality	Dummy	Macro-trip

The coefficient of the Alternative Specific Constant is negative, indicating the general inertia of car travellers to switch towards car sharing. As expected, the cost of private vehicle (BASE_cost) and car sharing (CS_cost) are both negative. As regards spatial and temporal attributes of the macro-trip, trips starting within Turin Municipality are more likely to be performed on car sharing (ORIG_TO); on the contrary, if the trip has a destination inside the city, the probability to switch to car sharing grows (DEST_TO). Jointly considered, these two aspects show that car sharing might potentially substitute car trips from suburbs towards the city of Turin. Furthermore, a trip destination within a limited traffic area produces a negative effect to the switching intention (LTZ); this reflects the lacking knowledge about car sharing advantages, since, in Turin, car sharing vehicles have free access to limited traffic zones. Furthermore, the switching probability rises if the macro-trip is performed on a non-working day, suggesting that car sharing can substitute private car not for systematics trips. Like the previous model, which considers all the currently adopted modes in the sample, the age of respondent has a positive effect (AGE), whereas being a retired person has a negative effect (D_RET). Moreover the switching probability increases if the interviewee has a high educational level (D_MPHD), owns a car sharing subscription (CS_pass) and lives in a household with a high income (HH_inc). Lastly, like in previous works, car sharing potential users tend to use active modes frequently, such as bike (F_bike).

Table 34. Switching model from private car towards car sharing

	Estimate	Std. Error	t test	p value	
Intercept_CS	-2.080	0.341	-6.11	0.000	***
CS_cost	-0.453	0.113	-4.02	0.000	***
BASE_cost	-0.291	0.096	-3.02	0.003	**
ORIG_TO	-0.259	0.135	-1.92	0.054	†
DEST_TO	0.290	0.136	2.13	0.033	*
LTZ	-1.480	0.759	-1.95	0.051	†
NOWORKDAY	0.445	0.208	2.14	0.033	*
AGE	0.011	0.006	1.86	0.063	†
D_RET	-0.767	0.249	-3.08	0.002	**
D_MPHD	0.313	0.151	2.07	0.039	*
CS_pass	2.130	0.419	5.08	0.000	***
F_bike	0.271	0.075	3.60	0.000	***
HH_inc	0.257	0.062	4.16	0.000	***

Significance codes: *** p< 0.001; ** p< 0.01; * p< 0.05; † p<0.10

Statistics

N = 1’085	
Init log likelihood:	-919.81
Final log likelihood:	-710.15
Likelihood ratio test for the init. model:	419.31
Rho-square for the init. model:	0.23
Rho-square-bar for the init. model:	0.21
Akaike Information Criterion:	1’446.30
Bayesian Information Criterion:	1’513.78

Switching model from public transport towards car sharing

The model presented in this section was calibrated selecting respondents who reported to have used public transport as travel mode for their macro-trip (530 interviews). The aim of this model is to identify variables affecting the switching intention towards car sharing. Exogenous variables are shown in Table 35, whereas model estimation results are represented in Table 36.

Table 35. Exogenous variables for the switching model from public transport to car sharing

	Description	Type	Level
Intercept_CS	Intercept for the car sharing alternative		
BASE_cost	Cost of the base alternative [€]	Metric	Macro-trip
BASE_dist	Trip length with the base alternative mode [km]	Metric	Macro-trip
BASE_wait	Waiting time at the transit stop for the base mode [min]	Metric	Macro-trip
BS_pass	Bike sharing subscription	Dummy	Individual
CS_cost	Cost of car sharing trip [€]	Metric	Macro-trip
D_RET	Retired *(ref. Working out of home)*	Dummy	Individual
D_WAH	Person working at home *(ref. Working out of home)*	Dummy	Individual
F_car	Frequency of use of car [times/week]	Metric	Individual
FEMALE	Female	Dummy	Individual
HH_car_licence	Number of car per driving licenced member	Metric	Household
NOWORKDAY	Non-working day	Dummy	Macro-trip

Like in the previously estimated models, the Alternative Specific Constant for car sharing is negative, highlighting the low willingness of respondents to change their travel habits. However, unlike the previous switching models, waiting time at the transit stop (BASE_wait) and trip length (BASE_dist), for the public transport base mode, are both significant and negative. This indicates that both waiting time and distance carried out on public means are significantly perceived by travellers as negative, affecting the choice to use public transport. Moreover car sharing tends to be adopted in non-working days (NOWORKDAY), indicating that it cannot substitute public transport for trips that are usually performed in other weekdays, such as systematic trips. As regards individual characteristics of potential car sharing users, females are more likely to switch to car sharing (FEMALE), rather than males; this might be due to the greater privacy and security provided by car sharing vehicles, respect to public transport, in which each trip is shared with other passengers. Furthermore, even if the age of interviewees was found to be not significant, being a retired person (D_RET) or a person working at home (D_WAH) has a negative effect on the switching intention. The coefficient of the former variable indicates that old people are not willing to shift to car sharing. Similarly, the coefficient of the latter is negative, since these persons usually have less mobility needs, which can be easily satisfied by public transport, respect to people working out of home. Moreover, potential car sharing users are also members of a bike sharing system (BS_pass), highlighting that they are familiar with sharing modes. In addition, they are also frequent car users, suggesting that their knowledge of car advantages and comfort might foster the switch from public transport. Focusing on the household level, if the average number of cars per member owing a driving licence grows (HH_car_licence), the probability to switch to car sharing decreases. This is an expected result, since if a licenced member has many available cars in her household, it is more likely that she uses those vehicles, rather than renting a car sharing vehicle.

Table 36. Switching model from public transport towards car sharing

	Estimate	Std. Error	t test	p value	
Intercept_CS	-2.240	0.414	-5.41	0.000	***
CS_cost	-0.367	0.167	-2.20	0.028	*
BASE_cost	-0.405	0.201	-2.02	0.044	*
BASE_wait	-0.034	0.018	-1.92	0.055	†
BASE_dist	-0.041	0.018	-2.33	0.020	*
NOWORKDAY	0.722	0.433	1.67	0.095	†
FEMALE	0.299	0.087	3.43	0.001	***
D_RET	-0.679	0.315	-2.15	0.031	*
D_WAH	-1.080	0.439	-2.45	0.014	*
BS_pass	1.470	0.673	2.19	0.029	*
F_car	0.658	0.267	2.46	0.014	*
HH_car_licence	-0.788	0.411	-1.92	0.055	†

Significance codes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; † $p < 0.10$

Statistics

N = 530	
Init log likelihood:	-372.91
Final log likelihood:	-215.76
Likelihood ratio test for the init. model:	314.30
Rho-square for the init. model:	0.42
Rho-square-bar for the init. model:	0.39
Akaike Information Criterion:	455.53
Bayesian Information Criterion:	506.98

Switching model from bike towards car sharing

In order to analyse variables affecting the choice to shift to car sharing of respondents reporting bike as the adopted mode for the macro-trip, a model was estimated considering only the corresponding interviews (72 interviews). Due to the limited size to calibrate the model, results could not be reliable. In particular, following the approach proposed by Louviere et al. (Louviere et al., 2003) and Hensher et al. (Hensher et al., 2005), the error of predicted probabilities obtained with the current sample size and a confidence level of 0.95, was estimated of 37%. Exogenous variables adopted in the final version of the model are described in Table 37, while Table 38 shows the results of model estimation.

Table 37. Exogenous variables for the switching model from bike to car sharing

	Description	**Type**	**Level**
Intercept_CS	Intercept for the car sharing alternative		
AGE	Age	Metric	Individual
BASE_dist	Trip length with the base alternative mode [km]	Metric	Macro-trip
CS_cost	Cost of car sharing trip [€]	Metric	Macro-trip
D_NHO	Not home based trip purpose *(ref. Home Based Work)*	Dummy	Macro-trip
F_car	Frequency of use of car [times/week]	Metric	Individual
F_pt	Frequency of use of public transport [times/week]	Metric	Individual
FEMALE	Female	Dummy	Individual
HH_cars	Number of cars	Metric	Household
HH_child	Number of underage children	Metric	Household
HH_inc	Income [1000€]	Metric	Household
HH_work	Number of employees	Metric	Household
PT_pass	Public transport subscription	Dummy	Individual

Unlike previously estimated models, the Alternative Specific Constant for car sharing is positive, suggesting that bikers are generally willing to use shared vehicles, instead of bikes, to perform the macro-trips. As expected, the length of bike trips (BASE_dist) has a negative effect on the choice of the bike. Respect to trips with a Home Based Work purpose, the coefficient of the variable related to Not Home Based Other trips is negative (D_NHO), albeit not so significant. This might suggest that bike trips starting from home and with systematic purpose could be substituted by car sharing. Moreover, the age of respondents has a negative effect (AGE), suggesting that young people are more willing to give up bike in favour of car sharing. Furthermore, females are less likely to adopt car sharing (FEMALE), rather than males. Potential users own a public transport subscription (PT_pass), even if they do not usually use the system so frequently (F_pt). On the contrary, they are frequent car drivers (F_car), suggesting that car advantages are often identified also in sharing vehicles. As regards socio-economic variables at household level, like in previous works, the number of owned cars has a negative effect (HH_cars) on the switching intention, conversely, coefficient related to household income is positive (HH_inc). Furthermore, the probability to choose car sharing increases, if the number of underage children increases (HH_child), and the number of employees decreases (HH_work). In conclusion, respondents who adopted bike and could potentially shift to car sharing tend to live in households with underage children, few employed members, a low number of cars and a high income level.

Table 38. Switching model from bike towards car sharing

	Estimate	Std. Error	t test	p value	
Intercept_CS	3.960	1.530	2.58	0.010	**
CS_cost	-1.560	0.557	-2.79	0.005	**
BASE_dist	-0.313	0.115	-2.72	0.006	**
D_NHO	-2.530	1.460	-1.74	0.083	†
AGE	-0.074	0.024	-3.04	0.002	**
FEMALE	-1.310	0.657	-1.99	0.046	*
PT_pass	1.990	1.100	1.81	0.071	†
F_car	0.819	0.277	2.96	0.003	**
F_pt	-0.432	0.252	-1.71	0.086	†
HH_cars	-1.590	0.892	-1.78	0.075	†
HH_child	0.922	0.514	1.79	0.073	†
HH_work	-1.250	0.675	-1.85	0.064	†
HH_inc	0.790	0.447	1.77	0.077	†

Significance codes: *** $p< 0.001$; ** $p< 0.01$; * $p< 0.05$; † $p<0.10$

Statistics

N = 72	
Init log likelihood:	-56.14
Final log likelihood:	-35.68
Likelihood ratio test for the init. model:	40.94
Rho-square for the init. model:	0.37
Rho-square-bar for the init. model:	0.13
Akaike Information Criterion:	97.35
Bayesian Information Criterion:	128.48

Switching model from walking towards car sharing

The aim of the model presented in this section is to understand factors affecting the switching intention from walking towards car sharing, in order to perform the macro-trip under analysis. To reach this aim, only interviewees who carried out the macro-trip on foot are considered; therefore 363 interviews were retained. Table 39 shows exogenous variables adopted for the model specification; estimation results are reported in Table 40.

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Table 39. Exogenous variables for the switching model from walking to car sharing

	Description	Type	Level
Intercept_CS	Intercept for the car sharing alternative		
BASE_dur	Duration of the trip with the base alternative mode [km]	Metric	Macro-trip
CS_pass	Car sharing subscription	Dummy	Individual
CS_walk_dist	Walking distance to reach the shared car [km]	Metric	Macro-trip
F_bike	Frequency of use of car [times/week]	Metric	Individual
HH_cars	Number of cars	Metric	Household
HH_child	Number of underage children	Metric	Household
HH_driv	Number of driving licenced	Metric	Household

The Alternative Specific Constant for car sharing has a negative coefficient, like in most of the previous models. As regards trip attributes, the walking distance to reach the car sharing vehicle is negative (CS_walk_dist), whereas car sharing cost is not significant; this indicates that these travellers perceive more this factor, rather than the cost of the trip. As expected, the duration of the macro-trip on foot (BASE_dur) has a negative effect on the choice of walking. Focusing on characteristics of the individual, the probability to switch to car sharing grows, if the respondent owns a car sharing subscription (CS_pass), suggesting that car sharing members are likely to use it in the future. Moreover, potential users tend to use active modes frequently, such as bike (F_bike). Lastly, like in other models, they live in households with few private cars (HH_cars), many licenced drivers (HH_driv), that might cause a competition to use available vehicles, and many underage children (HH_child).

Table 40. Switching model from walking towards car sharing

	Estimate	Std. Error	t test	p value	
Intercept_CS	-4.340	0.960	-4.52	0.000	***
CS_walk_dist	-0.756	0.000	-1.80	0.072	†
BASE_dur	-0.049	0.028	-1.77	0.077	†
CS_pass	2.250	0.740	3.04	0.002	**
F_bike	0.318	0.181	1.75	0.080	†
HH_cars	-1.150	0.437	-2.63	0.008	**
HH_child	0.993	0.302	3.29	0.001	**
HH_driv	1.060	0.405	2.61	0.009	**

Significance codes: *** p< 0.001; ** p< 0.01; * p< 0.05; † p<0.10

Statistics

N = 363	
Init log likelihood:	-241.22
Final log likelihood:	-71.49
Likelihood ratio test for the init. model:	339.45
Rho-square for the init. model:	0.70
Rho-square-bar for the init. model:	0.67
Akaike Information Criterion:	158.99
Bayesian Information Criterion:	189.80

Analysis of results of the logit models

In order to compare the effect of different factors on the choice to switch to car sharing, separately considering each base mode, estimated coefficients of exogenous variables of the four previous switching models are reported in Figure 24. In particular, this figure shows variables on the vertical axis and the values of the corresponding coefficients on the horizontal axis; moreover, each model corresponding to different currently adopted travel means is marked with a specific colour. Furthermore, white dots indicate the value of estimated coefficients, thicker lines represent the related standard errors and thinner lines the 95% confidence interval.

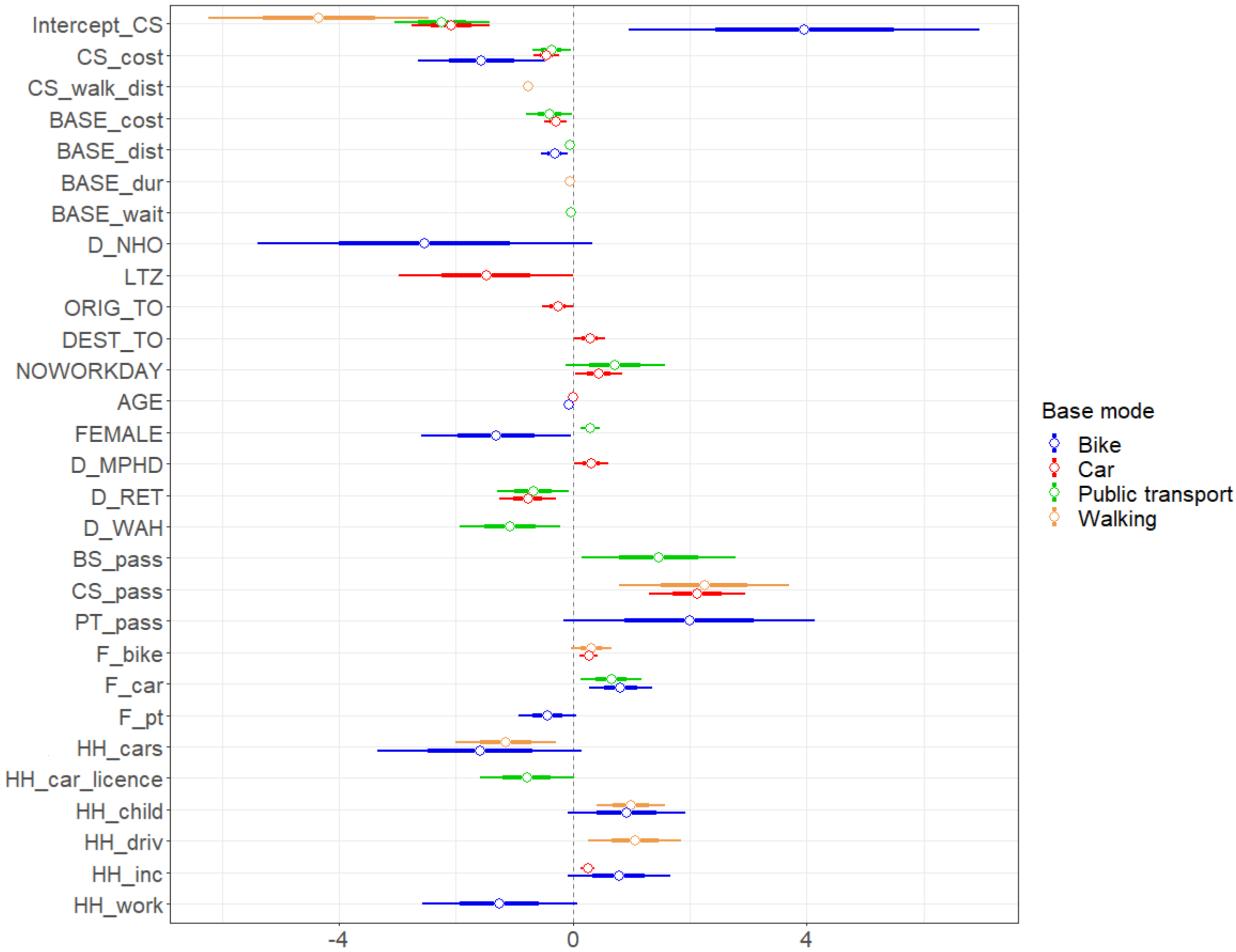

Figure 24. Comparative overview of estimated coefficients for each mode switching intention model

Observing Figure 24, one can note that the coefficient of the Alternative Specific Constant for car sharing (Intercept_CS) is positive only for bikers, suggesting a general willingness of bikers to switch towards car sharing. As regards attributes of the macro-trip, the cost of car sharing (CS_cost) is negative and significant for all the base modes, except for walking; this indicates that reducing service fare might induce shifts, not only from private car, but also from public transport and bike. In particular, bike has the highest absolute value of the cost coefficient, since the base of cost bike is null and, therefore, travellers perceive more the cost of car sharing. Moreover, walking distance to reach the nearest shared vehicle (CS_walk_dist) has a negative effect on the choice only for walkers; therefore, according to this observation, decreasing the capillarity of the service (e.g. by reducing the fleet of vehicles) might prevent the switch from walking to car sharing.

On the other hand, strategies to promote or avoid the switch can be focused also on changing the trip attributes of the base alternative. In particular, the shift of car drivers might be fostered by increasing the cost of private car usage (e.g. raising parking fares) (BASE_cost); on the contrary, the switch towards car sharing could be reduced by decreasing the public transport ticket cost (BASE_cost) and the waiting time at the transit stop (BASE_wait) (e.g. by increasing frequencies). In addition, free access to limited traffic zones (LTZ) seems not to be effective in promoting the shift from private car to car sharing, since drivers are not fully aware of this benefit. Furthermore, car sharing might substitute both private car and public transport in non-working days (NOWARKDAY) and, therefore, for non-systematic trips. On the contrary, non-mandatory bike trips are less likely to be substituted by car sharing (D_NHO). Moreover, car trips starting outside the city (ORIG_TO) and ending within the city (DEST_TO) might be potentially replaced by car sharing.

Focusing on individual and household characteristics, being a car sharing member (CS_pass) has a positive effect on the switching intention for car drivers and walkers, suggesting general satisfaction with the service. Potential users travelling by bike tend to be young (AGE); similarly, retired people (D_RET) using private car or public transport show a negative switching intention. This suggests that potential car sharing adopters are young or adult workers. Gender is significant only for bike and public transport (FEMALE). In particular, positive switches are estimated for female persons, due to the greater privacy and security provided by car sharing vehicles. On the contrary, women who used bike are less likely to switch. The educational level has an effect only on shifting intention from private car; specifically, a higher educational level (D_MPHD) increases the probability to switch.

As regards frequencies of use of travel means, one can note that the frequency of the base mode of each model is not an exogenous variable for that model, for instance, car frequency (F_car) does not affect the choice of car drivers to switch towards car sharing. This suggests that potential car sharing travellers tend to be multimodal, i.e. the does not use only the mode currently reported for the macro-trip under analysis.

Concerning characteristics at the household level, potential members using active modes (such as bike or walking) share similar coefficients of exogenous variables; in particular, they tend to live in households with underage children (HH_child) and few owned cars (HH_cars). Private cars play a negative effect even for public transport potential users; specifically, if the number of available cars for each driving licenced member in the household grows, the probability to switch decreases (HH_car_licence). This indicates that private car is the main obstacle to car sharing adoption for public transport users, bikers and walkers. Lastly, household income has a positive effect on switching intentions for both persons travelling by private car and bike. Understanding socio-economic attributes of potential car sharing users can be useful to effectively target the promotion of the service to specific segments of the population.

5.3.3. Decision Trees

Introduction

Data mining techniques in transportation

Data mining is described as the process to extract meaningful patterns, trends and rules from large datasets (Berry and Linoff, 2004; Han et al., 2012; Larose and Larose, 2015). According to this definition, outcomes of the approach should be understandable to analysists (Cios et al., 2007). One of the main tasks of data mining techniques is classification (Larose and Larose, 2015), which consists of analysing the attributes of a new object and assigning it to a class belonging to a predefined set (Berry and Linoff, 2004). With this aim, a model is trained on a preclassified set of items and then applied to unclassified data (Berry and Linoff, 2004). There are many methods to classify objects, such as Decision Tree, Neural Network, Naïve Bayesian Classification, Support Vector Machines and k-Nearest Neighbor Classification (Han et al., 2012). These models can be used also to make predictions (Berry and Linoff, 2004; Larose and Larose, 2015), i.e. to forecast the class to which a generic item belongs.

Recently, many authors adopted these approaches in the transportation field, in order to understand travel behaviour and to estimate significant parameters to predict future travel conditions in different scenarios (Chen et al., 2018). Some authors incorporated data mining techniques in 4-step models (Zenina et al., 2018), or in Activity-Based approaches (Lindner et al., 2017), to evaluate the choice of different travel patterns (Pitombo et al., 2011) and activities (Arentze and Timmermans, 2007). Furthermore, other works were focused on travel mode choice (Hagenauer and Helbich, 2017; Lindner et al., 2017), even comparing different data mining approaches. For instance, Xie et al. (Xie et al., 2007) adopted Decision Trees and Neural Networks to model travel mode choices for business trips. Lindner et al. (Lindner et al., 2017) used the same techniques to study motorized travel mode choice, taking into account multicollinear data. Zhang et al. (Zhang and Xie, 2008) estimated mode choice for commute trips with Support Vector Machines. Rashidi and Mohammadian (Rashidi and Mohammadian, 2011) used Decision Tree as trip generation and modal split model. Hagenauer and Helbich (Hagenauer and Helbich, 2017) applied Naïve Bayesian Classification, Support Vector Machines and Random Forest Decision Tree to model mode choice and compared the performances and results of the models.

Differences between data mining techniques and Random Utility Based models

The above mentioned data mining techniques differ from traditional models based on Random Utility Maximization Theory, in terms of approach, assumptions and interpretability. First of all, whereas econometric models are based on a specific theory, data mining techniques are data-driven approaches (Chen et al., 2018; Cios et al., 2007; Hagenauer and Helbich, 2017; Tang et al., 2015; Zhu et al., 2018), i.e. results are inferred directly from the input data (Lindner et al., 2017; Thill and Wheeler, 2007). From this perspective, these methods can be adopted to model travel behaviour of users, defining mode choice as a pattern recognition task in which multiple behavioural attributes, described by explanatory variables, determine the prediction of the choice among different alternatives (Lu and Kawamura, 2010; Pitombo et al., 2015; Xie et al., 2007; Zhang and Xie, 2008). Following this definition, data mining techniques can be applied both to reproduce existing scenarios (Pitombo et al., 2011; Wang and Kim, 2019), modelling users' choice based on current conditions and options (Yamamoto et al., 2007; Zhang et al., 2017), and to predict future travel behaviours (Pitombo et al., 2015).

Due to this different approach, assumptions under the two methodologies are quite different. In particular, Random Utility Based models require some statistical and mathematical assumptions on input data to calibrate them (Chen et al., 2018; Yamamoto et al., 2007). Moreover, the violation of these assumptions might lead to errors in the parameter estimation phase, with consequent biased model results (Chen et al., 2018; Hagenauer and Helbich, 2017; Lindner et al., 2017; Xie et al., 2007). Starting from the work of McFadden (McFadden, 1974), the Multinomial Logit Model has been widely adopted, however it requires the hypothesis of independence of irrelevant alternatives (IIAs) (Chen et al., 2018; Ermagun et al., 2015; Hagenauer and Helbich, 2017; Lindner et al., 2017; Tang et al., 2015; Xie et al., 2007), i.e. the effect of attributes are compensatory (Xie et al., 2007; Yamamoto et al., 2007). In order to overcome these drawbacks several more advanced models were implemented, such as probit models (Train, 2003). Furthermore, in order to introduce correlation effects among alternatives, nested logit, cross-nested logit, ordered generalized extreme values and mixed logit models were implemented (Tang et al., 2015; Zhu et al., 2018). However, the linear structure of the utility function might limit the capability of modelling complex decisions (Lee et al., 2018; Xie et al., 2007; Zhu et al., 2018); in particular, non-linear interactions among exogenous variables are to be beforehand specified in the utility function (Pinjari and Bhat, 2006).

On the contrary, data mining techniques do not require any statistical and mathematical assumption on data structure (Chang and Chen, 2005; Tang et al., 2015; Thill and Wheeler, 2007; Wang and Kim, 2019; Zhang et al., 2017), overcoming some of the previously explained drawbacks (Lindner et al., 2017). Therefore, they have a flexible structure (Tang et al., 2015; Wang and Ross, 2018; Xie et al., 2007; Yamamoto et al., 2007; Zenina et al., 2018), which can be applied to different datasets. Furthermore, correlations among independent variables do not affect these techniques (Lu and Kawamura, 2010). Moreover, any functional form and interaction among alternatives are not to be specified a priori by the analyst, but they are inferred from the input data (Chang and Chen, 2005; Thill and Wheeler, 2007). In addition, they can easily manage large databases (Zhu et al., 2018), even with imbalanced data (Tang et al., 2015; Wang and Ross, 2018).

Some author compared performances and results of data mining techniques with traditional logit models. Both Wets et al. (Wets et al., 2000) and Pitombo et al. (Pitombo et al., 2015) compared Decision Tree algorithms and Multinomial Logit models, concluding that the two techniques had similar prediction performances. On the other hand, Zhang and Xie (Zhang and Xie, 2008) obtained that Support Vector Machines performed better than Multinomial Logit in modelling travel mode choice. Furthermore, Lindner et al. (Lindner et al., 2017) applied a Classification Tree, an Artificial Neural Network and a binary logit to multicollinear data, in order to evaluate motorized travel mode choice; the authors observed that the two data mining approaches had a better accuracy and do not require an a priori multicollinearity analysis. Lee et al. (Lee et al., 2018) compared four types of Artificial Neural Networks with a Multinomial Logit Model for mode choice analysis, obtaining that the formers outperformed the latter in terms of prediction accuracy. Ermagun et al. (Ermagun et al., 2015) found that Random-Forest Decision Tree produced more accurate results rather than Nested Logit, to investigate travel mode choice for educational purposes. Chapleau et al. (Chapleau et al., 2019) came to similar results with a Random Forest Decision Tree and a Multinomial Logit.

Despite the better predictive accuracy of data mining approaches, they have not widely adopted since, working as a black box (Wang and Kim, 2019), they often lack of interpretability (Ermagun et al., 2015; Waddell and Besharati-Zadeh, 2019; Zhang and Xie, 2008). In particular, if compared with traditional econometric models, it is not possible to interpret the sign and significance of coefficients of exogenous variables, within a theoretical framework (Waddell and Besharati-Zadeh, 2019). Moreover, results that are quite useful for planning and forecasting purposes and that are commonly derived through an econometric approach, such as the Value Of Time and demand elasticities, cannot be directly obtained from such techniques (Chang and Chen, 2005; Zhang and Xie, 2008; Zhu et al., 2018). From this perspective, they tend to focus more on predictive accuracy rather than on counterfactual analysis of potential impacts of different policies (Waddell and Besharati-Zadeh, 2019).

However, recently, some authors were able to extract interpretable economic information, such as elasticities, from a data mining approach (Wang and Zhao, 2018). Furthermore, other authors developed sensitivity analyses on independent variables to understand their effect (Wang and Kim, 2019). Moreover, data mining techniques are very sensitive to training data (Wets et al., 2000; Zhu et al., 2018). Due to the previously explained differences, data mining methods have both advantages and disadvantages, if compared with econometric models. In conclusion, data mining techniques cannot be considered as methods substituting Random Utility Based models, but as different approaches to study a given problem from a different perspective.

Decision Trees in transportation

Among different data mining techniques, in this work, Decision Tree approach was adopted for the following reasons. First of all, Decision Tree algorithms produce an output which is easier to be interpreted (Lu and Kawamura, 2010; Yamamoto et al., 2007), if compared with other data mining methods, such as Support Vector Machines (Wang and Kim, 2019; Zhang and Xie, 2008) and Artificial Neural Networks (Lindner et al., 2017; Xie et al., 2007). In particular, this approach provides a visual representation of results, which can be interpreted as if-then rules (Berry and Linoff, 2004; Xie et al., 2007), leading to a better understanding of the effect of explanatory variables on the travel behaviour of users (Chang and Chen, 2005; Lindner et al., 2017; Tang et al., 2015; Yamamoto et al., 2007). Moreover, Decision Tree can be considered as a function that uses a vector of attributes as an input variable, and it returns a decision value, after a series of tests (Lindner et al., 2017; Russell and Norvig, 2002). Specifically, the algorithm derives if-then rules which, based on exogenous conditions (such as trip attributes or characteristics of the travellers), predict a discrete dependent variable, i.e. respondent’s decision (Thill and Wheeler, 2007). According to this perspective, the general structure of the algorithm simulates the cognitive and decisional process of users (Arentze and Timmermans, 2003, 2004; Thill and Wheeler, 2007).

However, different Tree structures might fit the same input dataset and small changes in an independent variable might lead to different Decision Trees (Wets et al., 2000). In addition, unlike logit models, Decision Tree predicts discontinuous effects on a continuous variable (Wets et al., 2000), making the estimation of elasticities quite difficult (Arentze and Timmermans, 2007). Moreover, like other data mining models, Decision Trees tend to predict the class with the majority of observations in the calibration dataset, neglecting classes with few items (Chapleau et al., 2019; Tang et al., 2015; Xie et al., 2007). Furthermore, Decision Tree structure can be affected by repetition and replication problems, which might lead to a difficult interpretation of outcomes; the former occurs when the same attribute appears more than one time along a branch of the tree, whereas the latter occurs when some subtrees are duplicated within the overall tree (Han et al., 2012).

Despite these drawbacks, Decision Trees have been adopted by several authors to model travel mode choice of users (Arentze and Timmermans, 2007; Oral and Tecim, 2013; Tang et al., 2015; Wets et al., 2000). Wets et al. (Wets et al., 2000) tested different algorithms to evaluate travel mode choice in the context of a wide activity scheduling model, using travel diaries in the Netherlands. Xie et al. (Xie et al., 2007) calibrated a Decision Tree with travel diaries, to investigate business travel mode choice in San Francisco Bay Area (California). Tang et al. (Tang et al., 2015) adopted this technique to study the mode switching behaviour of travellers, managing a class imbalance issue, using Revealed-preferences data in Washington (United States). Hagenauer and Helbich (Hagenauer and Helbich, 2017) calibrated different Decision Tree algorithms with travel diary data in the Netherlands, performing sensitivity analysis and comparing the obtained results and performances. Zhang et al. (Zhang et al., 2017) used a Tree-based regression model to understand school travel mode choice in Beijing (China). Recently, Chapleau et al. (Chapleau et al., 2019) modelled travel mode choice of users in the Greater Montreal Area (Canada) through Random-Forest Decision Tree, which was calibrated on a large travel survey, carried out in 2008, and then applied to a large dataset of trips obtained in 2013. Other authors embedded Decision Trees algorithms in a 4-step (Zenina et al., 2018) or activity-based model (Arentze and Timmermans, 2007). Furthermore, Decision Trees was adopted as a part of a more extensive mode choice model, to define groups of people with homogeneous travel behaviours (Zhang et al., 2017) or to identify the most important variables for further analysis (Pitombo et al., 2015). Several authors compared the predictive performances of this method with traditional logit models, obtaining that the former outperformed the latter (Chen et al., 2018; Hagenauer and Helbich, 2017; Lindner et al., 2017; Moons et al., 2007; Sekhar et al., 2016; Xie et al., 2007; Yamamoto et al., 2007). However, the use of a Decision Tree to define variables affecting car sharing adoption is very limited. In particular, only Wang et al. (Wang et al., 2017) adopted a Hierarchical Tree-based Regression to investigate the most important socio-economic characteristics of users and trip attributes that might affect the choice to adopt a car sharing electric vehicle. Nevertheless, they did not consider the mode that was previously adopted by users. Moreover, data used to calibrate the model were obtained from individuals that were not representative of the overall population of the study area.

Decision Tree: description and algorithms

Decision Tree is a classification method, which consists of a flowchart-like tree structure (Han et al., 2012) representing a set of decision rules adopted to separate a heterogeneous population into smaller and more homogeneous groups, according to a specific target class (Berry and Linoff, 2004). In particular, the general structure of the Tree consists of nodes connected by branches (Cios et al., 2007). Each internal node [also called decision node (Cios et al., 2007)] represents a test on a specific attribute or feature, whereas each branch identifies an outcome of the test (Han et al., 2012). Each decision node has many children nodes (Cios et al., 2007). The first decision node is the root node, which is set at the top of the tree (Cios et al., 2007; Han et al., 2012); the nodes at the bottom of the tree are called leaves and are labelled with the predicted classes (Han et al., 2012). Following this framework, the path from the root node to a leaf node defines the set of rules which lead to the prediction of the class of that leaf (Berry and Linoff, 2004; Han et al., 2012).

The overall aim of the algorithm is to split the set of observations into subsets, each of them containing examples belonging to a single class (Cios et al., 2007). One of the main characteristics of these subgroups is purity. High purity of a subgroup means that internal examples of a single class predominate, whereas a low purity level means that the subgroup contains a representative distribution of classes (Berry and Linoff, 2004).

In order to reach this aim, different algorithms were developed, however they are based on the following common procedure (Berry and Linoff, 2004; Cios et al., 2007). They start considering each input variable in turn, then, they try to split it, measuring the increasing of impurity derived from that split. After that, they repeat this procedure for all the input variables and they select the one that produces the best split. This variable is chosen for the initial split, generating two or more children nodes. Then, each node is recursively split following the same procedure. The recursively partitioning stops if one of the following conditions is satisfied (Han et al., 2012): all the records in the node belong to the same class (Cios et al., 2007; Han et al., 2012), the node contains a number of observations lower than a specified threshold (Han et al., 2012), or no subsequent splits make an improvement (Berry and Linoff, 2004). After the stop, the non-split node becomes a leaf node (Berry and Linoff, 2004), which is labelled with the predicted class, i.e. the class with the higher number of corresponding observations (Han et al., 2012). If a completely deterministic relationship between the input variables and the target existed, the procedure would generate only pure leaves (Berry and Linoff, 2004). The improvement of each split is measured through the effect on node purity, in terms of the target variable, therefore the splitting criterion should be selected according to the type of class labels (Berry and Linoff, 2004). Since, in the present work, the target variable is the travel mode, only splitting criteria used for categorical variables are presented. Each developed algorithm which implements Decision Trees differs according to the splitting criterion (Arentze and Timmermans, 2007).

The notation adopted herein is as follows (Han et al., 2012). Let N be a data partition, i.e. the training set of n class-labelled examples contained in a node. Let N_j (for j = 1, …, k) be a partition of n_j obtained from the split of N, and contained in a leaf node. Let C_i (for i = 1, …, m) a generic class. Let A be a generic input attribute (or feature) of the training set. The aim of the following measures is to find the attribute A which produces the best split of node N into k child nodes (N_j).

The Gini index considers the probability that two randomly chosen examples in the population belong to the same class. The purity of a node N is calculated as:

$$GINI(N) = 1 - \sum_{i=1}^{m} p^2(C_i|N)$$

Where $p^2(C_i|N)$ is the frequency of class C_i at node N. This index ranges from 0, if all examples belong to a single class (low node impurity) and $1 - \frac{1}{m}$, if all examples are equally distributed among all the m classes (high node impurity) (Berry and Linoff, 2004; Cios et al., 2007). The quality of the split for a given attribute A is computed as:

$$GINI_A(N) = \sum_{j=1}^{k} \frac{n_j}{n} GINI(N_j)$$

The reduction of impurity after the split of node N on attribute A is the difference between the index value of the parent node and the index value after the split:

$$\Delta GINI(A) = GINI(N) - GINI_A(N)$$

In the case of continuous attributes, values of A are sorted in increasing order and the midpoint between two consecutive values is a potential split-point. After that, the node N is split into two partitions ($k = 2$), where N_1 is the child node with all the examples with values of attribute A less or equal to the split-point, whereas N_2 contains the remaining examples (Han et al., 2012). This index is adopted in CART algorithm (Classification and Regression Trees), which was developed by Breiman et al. (Breiman et al., 1984).

Entropy index is based on information theory, which studies the information content of a message (Han et al., 2012). This splitting criterion is adopted in Iterative Dichotomizer 3 algorithm (ID3), proposed by Quinlan (Quinlan, 1986). According to this theory, the information conveyed by a message depends on its probability, measured in bits as the negative logarithm to base 2 of that probability (Wets et al., 2000). The splitting criterion aims to minimize the number of tests required to classify a set of examples, ensuring that a simple structure of the tree is obtained (Han et al., 2012). Therefore, the expected information (or entropy) needed to classify a data partition N is defined as:

$$Info(N) = -\sum_{i=1}^{m} p(C_i|N) \log_2 p(C_i|N)$$

Where $p^2(C_i|N)$ is the frequency of class C_i at node N. This index ranges from 0, if all examples belong to the same class, and $\log_2 m$, if the examples are equally distributed among all the classes. Like for the Gini index, the reduction of information achieved by the split of node N, after partitioning on attribute A, is calculated as:

$$Gain_A(N) = Info(N) - \sum_{j=1}^{k} \frac{n_j}{n} Info(N_j)$$

According to this index, the attribute that produces the highest information gain is chosen for the split of the node; in other words, the split based on that attribute ensures that the minimum amount of information is required to classify the examples in that node (Han et al., 2012). If A is a continuous attribute the same procedure of the split following Gini index is adopted. This index is called Information gain.

However, Information gain index is biased towards cases with many outcomes (Cios et al., 2007), i.e. it tends to prefer splits leading to a large number of partitions, which contain few examples, but are pure (Berry and Linoff, 2004), since the information gain for these splits is maximum (Han et al., 2012). In order to overcome this drawback, C4.5 algorithm developed by Quinlan (Quinlan, 1993) adopts the Gain ratio, which is based on the Split information, defined as follows:

$$SplitInfo_A(N) = -\sum_{j=1}^{k} \frac{N_j}{N} \log_2 \left(\frac{N_j}{N}\right)$$

This measure evaluates the potential information produced by the split of node N into k child nodes on attribute A; moreover, it considers the proportion of examples in each child node N_j over the total number of examples in the parent node N (Han et al., 2012). The Gain ratio is calculated as:

$$GainRatio_A(N) = \frac{Gain_A(N)}{SplitInfo_A(N)}$$

This index penalizes partitioning with high entropy, overcoming the disadvantage of Information gain (Berry and Linoff, 2004), however a constraint is added to avoid that the Information gain is null. In particular, the C4.5 algorithm chooses the attribute for the split which generates the highest value of Gain ratio, but subject to the constraint that the Information gain must be at least as large as the average information gain over all possible tests (Han et al., 2012; Wets et al., 2000).

Some other measures to evaluate the best split were proposed (Han et al., 2012), such as in the CHAID algorithm (Kass, 1980), which adopts a Chi-square (χ^2) statistical test, but it can be applied only to categorical variables (Berry and Linoff, 2004).

Decision Trees might be affected by overfitting problems, i.e. general patterns are estimated at big nodes, whereas patterns specific only to the training set are found in smaller nodes (Berry and Linoff, 2004). Therefore lower parts of the tree became unreliable (Wets et al., 2000). Moreover, the tree is unstable (Berry and Linoff, 2004) and very large, with potential problems to read the resulting tree (Cios et al., 2007). In order to overcome this drawback, pruning techniques were developed (Berry and Linoff, 2004; Cios et al., 2007; Han et al., 2012). The aim of these methods is to remove the least reliable branches of the tree, obtaining a simpler tree (Han et al., 2012), without reducing the overall classification accuracy (Cios et al., 2007). Pruning techniques are divided into pre-pruning and post-pruning, depending on when the pruning method is applied during the process of building a tree (Cios et al., 2007). Pre-pruning occurs when the growth of the tree is stopped since further splits do not improve impurity measures (Han et al., 2012). On the contrary, following a post-pruning approach, a subtree starting from a node is removed from the whole tree and it is substituted with a leaf, which is labelled with the majority class of examples in the subtree (Han et al., 2012).

CART adopts a cost complexity post-pruning algorithm, which considers the error rate, i.e. the percentage of misclassified examples in a node (Han et al., 2012). Starting from the bottom of the tree, this method calculates, for each internal node, the cost complexity of the subtree at that node and the cost complexity if the subtree at that node were pruned. If the pruned subtree produces a smaller cost complexity, then the subtree is removed. The cost complexity is estimated considering a pruning set of labelled examples, which is independent of the training set used to build the unpruned tree and of the dataset selected to estimate model accuracy (Han et al., 2012). On the other hand, C4.5 adopts a pessimistic pruning strategy, which considers the error rate to evaluate the subtree removal, like CART; however, error rates are calculated directly from the training dataset, without using a pruning set. Moreover the error rates are adjusted by adding a penalty, based on a specified confidence level, in order to avoid the bias due to the optimistic accuracy or error obtained from the whole training set (Han et al., 2012). Pre-pruning and post-pruning can be combined, even if the latter is more computationally expensive, but it leads to more reliable results (Han et al., 2012).

Like other data mining techniques, Decision Trees tend to easily classify classes with many examples, but neglecting those with few examples (Wets et al., 2000; Xie et al., 2007). Therefore, in order to deal with imbalanced datasets, different techniques were proposed. The first approach consists in creating a training set by undersampling observations belonging to the majority class or by oversampling examples belonging to the minority class, introducing synthetic examples (Chawla et al., 2002; Tang et al., 2015). Following another approach, weights are added to each observation (Chapleau et al., 2019; Xie et al., 2007); in particular, low weights are associated to examples belonging to the majority class, in order to balance the dataset. The last method consists in introducing a loss matrix, to increase the ability of the classifier to discern observations belonging to the minority class (Tang et al., 2015). In this work, a balance weight procedure was followed, since oversampling or undersampling techniques might undermine the representativeness of the sample, moreover there were no sound criteria to choose values for the loss matrix. In particular, weights were added in such a way that the sum of example weights of all classes is the same. This approache improves the ability of the algorithm to identify classes with few elements (Chapleau et al., 2019).

In the present work, the C4.5 algorithm was adopted to generate Decision Trees, since, unlike CHAID, it can deal with both categorical and continuous data (Xie et al., 2007). Moreover, unlike CART, it is not restricted to binary splits at each node (Berry and Linoff, 2004; Larose and Larose, 2015; Pitombo et al., 2011; Xie et al., 2007). Furthermore, it has a splitting criterion different rather than CART, as explained before. In addition, this algorithm considers also weighted observations. However, it generates one branch for each categorical attribute, therefore leaves with no examples might be generated (Larose and Larose, 2015). The C4.5 algorithm was first used to study travel behaviour of users by Wets et al. (Wets et al., 2000), who adopted Decision Trees for mode choice analysis.

Decision Trees for the current analyses

In the developed application, the macro-trips reported by users are the examples to be classified, whereas the classes correspond to the choice of users in the Stated-preferences experiments. Attributes of each example are the socio-economic characteristics of travellers and the attributes of the trip chain. Therefore, the aim of Decision Trees described in this section is to predict the switching intention for each macro-trip.

In order to reach this target, many Decision Trees were estimated, following the approach shown in Figure 25. The first one considers all the macro-trips, independently on the mode currently reported in the Revealed-preferences part of the survey. In addition, other Decision Trees were generated by separately considering the chained trips performed with only one travel mode (car, public transport, bike and walking). Thus, four Decision Trees were implemented and analysed to identify variables affecting the switching decision. Furthermore, two groups of Decision Trees were estimated, depending on the input variables adopted (Table 41). The first set considers all socio-economic characteristics of users at household and individual level, and absolute values of trip attributes, both for the base mode, i.e. the mode reported by travellers, and for car sharing alternative. In particular, exogenous variables are the same selected for logit models described in the previous section; in this way, it is possible to compare the results of the two approaches. For the second group of Trees, in order to study how respondents compare the car sharing trip with the one with the base mode, differences between trip attributes with the two travel means were considered as independent variables. Tang et al. (Tang et al., 2015) followed this approach to evaluate the difference between the Level Of Service of two alternative modes. However, unlike previous studies, in this work, Decision Trees were estimated to select trips attributes that might affect the choice to perform a trip on car sharing, diversifying the analysis according to the mode currently adopted by users, in order to consider the effects of the original means. Results of the two groups of models might differ since, in the first case, the currently adopted mode is considered as an exogenous variable, whereas, in the second case, the original mode is the criterion to select the calibration sample. The latter approach reflects the binary choice task which was administered to each respondent; in particular, this method simulated the real mode choice that an individual has to face when she has to select between the specific adopted travel mode and car sharing. The entire procedure was developed using RapidMiner Studio software and Weka extension (Hofmann and Klinkenberg, 2013).

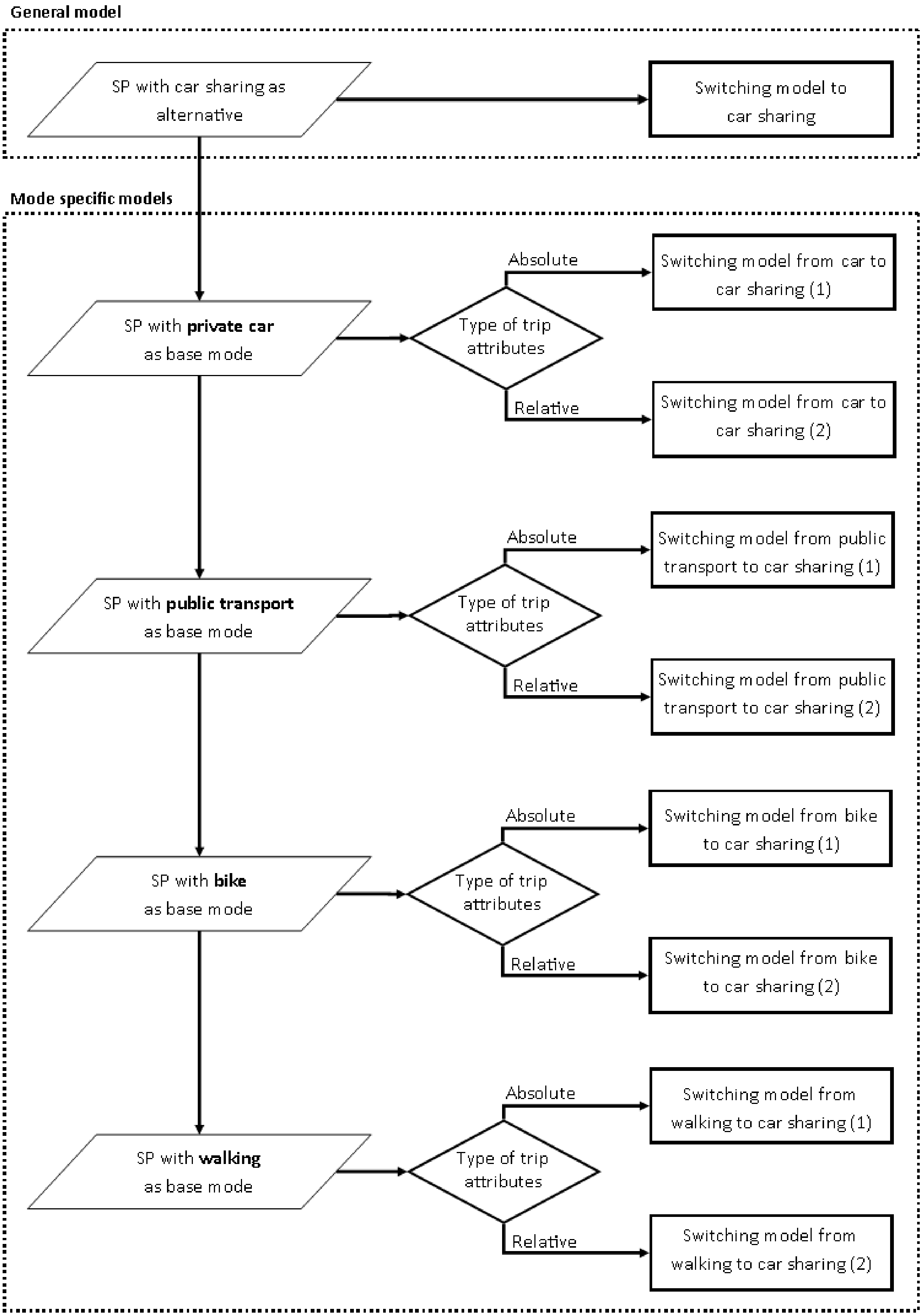

Figure 25. Flow chart describing the implemented Decision Trees

Table 41. Exogenous variables for Decision Trees

	Description	Type	Level
AGE	Age	Metric	Individual
BASE_cost	Cost of the base mode [€]	Metric	Macro-trip
BASE_dist	Trip length with the base mode [m]	Metric	Macro-trip
BASE_dur	Trip duration with the base mode [min]	Metric	Macro-trip
BASE_MODE	Mode reported by travellers (Car, Public transport, Bike, Walking)	Categorical	Macro-trip
BASE_wait	Waiting time for the vehicle with the base mode [min]	Metric	Macro-trip
BASE_walk_dist	Walking distance to reach the vehicle of the base mode [m]	Metric	Macro-trip
BASE_walk_dur	Walking time to reach the vehicle of the base mode [min]	Metric	Macro-trip
BS_pass	Bike sharing subscription (1: Yes, 0: No)	Categorical	Individual
CS_cost	Cost of car sharing trip [€]	Metric	Macro-trip
CS_dist	Trip length with car sharing [m]	Metric	Macro-trip
CS_dur	Duration of car sharing trip [min]	Metric	Macro-trip
CS_pass	Car sharing subscription (1: Yes, 0: No)	Categorical	Individual
CS_walk_dist	Walking distance to reach the shared car [km]	Metric	Macro-trip
CS_walk_dur	Walking distance to reach the shared vehicle [min]	Metric	Macro-trip
DELTA_cost	Difference between the cost of the trip on car sharing and the base mode [€]	Metric	Macro-trip
DELTA_dist	Difference between the length of the trip on car sharing and the base mode [m]	Metric	Macro-trip
DELTA_dur	Difference between the duration of the trip on car sharing and the base mode [min]	Metric	Macro-trip
DELTA_wait	Difference between the waiting time for car sharing and the base mode [min]	Metric	Macro-trip
DELTA_walk_dist	Difference between the walking distance to reach the vehicle of car sharing and of the base mode [m]	Metric	Macro-trip
DELTA_walk_dur	Difference between the walking time to reach the vehicle of car sharing and of the base mode [min]	Metric	Macro-trip
DEST_TO	Trip destination within Turin Municipality (1: Yes, 0: No)	Categorical	Macro-trip
EDU_LEV	Educational level (NHS: Not high school graduated, HS: high school graduated, MP: Master's Degree or Ph.D. graduated)	Categorical	Individual
F_bike	Frequency of use of bike [times/week]	Metric	Individual
F_bs	Frequency of use of bike sharing [times/week]	Metric	Individual
F_car	Frequency of use of car [times/week]	Metric	Individual
F_pt	Frequency of use of public transport [times/week]	Metric	Individual
GENDER	Gender (M: Male, F: Female)	Categorical	Individual
HH_car_licence	Number of cars per driving licenced member	Metric	Household
HH_cars	Number of cars	Metric	Household
HH_driv	Number of driving licenced	Metric	Household
HH_inc	Income [1000€]	Metric	Household
HH_memb	Number of members	Metric	Household

HH_work	Number of employed members	Metric	Household
LTZ	Trip destination within a Limited Traffic Zone (1: Yes, 0: No)	Categorical	Macro-trip
NOWORKDAY	Trip performed in a non-working day (1: Yes, 0: No)	Categorical	Macro-trip
OCC_LEV	Occupational status (WOOH: worker out of home, WAH: worker at home, STN: student, RET: retired, UNE: unemployed)	Categorical	Individual
ORIG_TO	Trip origin outside Turin Municipality (1: Yes, 0: No)	Categorical	Macro-trip
PARK_HOME	Private parking near home (1: Yes, 0: No)	Categorical	Individual
PARK_WORK	Private parking near working place (1: Yes, 0: No)	Categorical	Individual
PT_pass	Public transport subscription (1: Yes, 0: No)	Categorical	Individual
TRIP_PURP	Trip purpose (HBW: Home Base Work, HBEd: Home Based Education, HBO: Home Based Other, NHO: Not Home Based Other, NHB: Not Home Based Business)	Categorical	Macro-trip

Switching model from all modes towards car sharing

In this Decision Tree, all the answers belonging to the training sample were used to calibrate the model; moreover, in this case, the mode currently adopted by respondents to perform the macro-trip is considered as an exogenous variable. Visual representations of the calibrated Decision Tree are reported in Appendix B.1 (Figure 47, which was divided into Figure 48, Figure 49 and Figure 50, for the sake of readability), whereas Table 42 exhibits the corresponding textual description. Observing Figure 47 (Figure 48, Figure 49 and Figure 50) one can note that (CS_pass) is the root node, which represents the most important variable; therefore, if a respondent owns a car sharing pass, she might switch to car sharing; after that leaf there are not any more leaves, indicating that car sharing members are more willing to use the service again in the future. The second most important variable is the number of employees in the household (HH_work), which is related to the income level. Individuals living in households with no employed members are likely to be retired people. They are willing to switch to car sharing if they are frequent car drivers (F_car) with a cost of the trip with a base alternative greater than 0.13 euros (BASE_cost).

For households with at least one employed member, the Decision Tree shows that car sharing can substitute bike trips but not walking trips (BASE_MODE), since trips on foot might have not appropriate characteristics for car sharing. This was suggested by the highest percentage of negative switches, respect to the other base modes, in the Stated-preference experiments (Section 4.5). As regards the relationship with public transport, travellers might switch to car sharing if the waiting time (BASE_wait) is greater than 4 minutes. Furthermore, trips carried out in non-working days (NOWORKDAY) are more likely to be performed by car sharing rather than public transport, since the frequency of the latter service might be low. Moreover, car sharing can replace public transport even for systematic (HBW) and non-systematic (HBO) home based trips, if travellers frequently adopt private car, since they are more likely to be aware of the advantage of driving a vehicle, if compared with public transit (e.g. flexibility, privacy and comfort). A similar result was suggested by the high number of frequent car users among car sharing members, reported in (Section 4.4).

Considering macro-trips which were performed on private car, they might be substituted by car sharing if respondents have a high income level (HH_inc) and no reserved parking at home (PARK_HOME). Moreover potential car sharing users who drove a car own a public transport subscription (PT_pass), suggesting that they tend to have multimodal habits and are used to share a vehicle with other persons, as indicated by statistical analysis of the sample of car sharing members (Section 4.4). Like in the corresponding logit model, potential substitution patterns are shown also for car trips ending outside the city of Turin (DEST_TO), for people not owing a public transport pass; therefore, these persons might consider car sharing as an alternative both to private car but also to public transport. Moreover, users are not willing to switch to car sharing if the cost of the macro-trip (CS_cost) is higher than 2.7 euros. Like in the previous logit model, age plays has a positive effect on the switching intention, since people aged 43 or more (AGE) and with more than one underage children (HH_child) (as obtained from descriptive statistics about car sharing members in (Section 4.4), report to shift to car sharing. Furthermore, travellers tend to switch if they had to walk to reach their private car for more than 4 minutes. In addition, one can note that users are willing to adopt car sharing even if they live in households with more than one private available car (HH_car).). Lastly, car drivers are willing to perform their macro-trip on car sharing if it starts inside the city and the corresponding duration (BASE_dur) is greater than 27 minutes.

Furthermore positive switches are predicted if the walking time to reach the vehicle of the base alternative is null, suggesting that potential car sharers might not be willing to walk to reach a shared vehicle. Positive predicted switches are often associated with high values of usage frequencies of different travel modes, highlighting that car sharing potential users tend to have multimodal travel habits.

Table 42. Structure of the Decision tree for switching intentions towards car sharing

```
CS_pass = 0
|   HH_work <= 0
|   |   F_car <= 2: BASE (137.1/27.27)
|   |   F_car > 2
|   |   |   BASE_cost <= 0.129: BASE (17.21/2.27)
|   |   |   BASE_cost > 0.129
|   |   |   |   BASE_walk_dur <= 0: CSHAR (20.37/5.6)
|   |   |   |   BASE_walk_dur > 0: BASE (25.99/11.36)
|   HH_work > 0
|   |   BASE_MODE = Car
|   |   |   HH_inc <= 2.75
|   |   |   |   PT_pass = 0
|   |   |   |   |   PARK_HOME = 1
|   |   |   |   |   |   F_bike <= 0
|   |   |   |   |   |   |   CS_cost <= 2.7
|   |   |   |   |   |   |   |   HH_child <= 1
|   |   |   |   |   |   |   |   |   BASE_walk_dur <= 4
|   |   |   |   |   |   |   |   |   |   BASE_walk_dur <= 1
|   |   |   |   |   |   |   |   |   |   |   HH_work <= 1
|   |   |   |   |   |   |   |   |   |   |   |   HH_cars <= 1: BASE (19.57/6.82)
|   |   |   |   |   |   |   |   |   |   |   |   HH_cars > 1: CSHAR (22.33/5.29)
|   |   |   |   |   |   |   |   |   |   |   HH_work > 1
|   |   |   |   |   |   |   |   |   |   |   |   ORIG_TO = 1
|   |   |   |   |   |   |   |   |   |   |   |   |   BASE_dur <= 27: BASE (10.98/2.27)
|   |   |   |   |   |   |   |   |   |   |   |   |   BASE_dur > 27: CSHAR (12.31/4.36)
|   |   |   |   |   |   |   |   |   |   |   |   ORIG_TO = 0: BASE (20.83/3.41)
|   |   |   |   |   |   |   |   |   |   BASE_walk_dur > 1: BASE (24.67/2.27)
|   |   |   |   |   |   |   |   |   BASE_walk_dur > 4: CSHAR (28.14/9.96)
|   |   |   |   |   |   |   |   HH_child > 1
|   |   |   |   |   |   |   |   |   AGE <= 43: BASE (10.46/4.55)
|   |   |   |   |   |   |   |   |   AGE > 43: CSHAR (10.34/1.24)
|   |   |   |   |   |   |   CS_cost > 2.7: BASE (11.2)
|   |   |   |   |   |   F_bike > 0
|   |   |   |   |   |   |   DEST_TO = 1
|   |   |   |   |   |   |   |   BASE_walk_dur <= 0: CSHAR (10.13/2.18)
|   |   |   |   |   |   |   |   BASE_walk_dur > 0: BASE (12.32/4.55)
|   |   |   |   |   |   |   DEST_TO = 0: CSHAR (27.61/7.16)
|   |   |   |   |   PARK_HOME = 0: CSHAR (46.24/15.56)
|   |   |   |   PT_pass = 1: CSHAR (28.54/8.09)
|   |   |   HH_inc > 2.75: CSHAR (170.53/46.67)
|   |   BASE_MODE = Walking: BASE (79.37/19.32)
|   |   BASE_MODE = Bike: CSHAR (26.8/10.89)
|   |   BASE_MODE = Public transport
|   |   |   F_bs <= 0
|   |   |   |   BASE_wait <= 4: BASE (42.38/9.09)
|   |   |   |   BASE_wait > 4
|   |   |   |   |   NOWORKDAY = 0
|   |   |   |   |   |   TRIP_PURP = HBW
|   |   |   |   |   |   |   F_car <= 0.5: BASE (10.36/2.27)
|   |   |   |   |   |   |   F_car > 0.5: CSHAR (18.83/7.47)
|   |   |   |   |   |   TRIP_PURP = HBO
|   |   |   |   |   |   |   F_car <= 0: BASE (11.3/2.27)
|   |   |   |   |   |   |   F_car > 0: CSHAR (30.63/12.45)
|   |   |   |   |   |   TRIP_PURP = NHO: BASE (1.87)
|   |   |   |   |   |   TRIP_PURP = NBEd: CSHAR (1.14)
|   |   |   |   |   |   TRIP_PURP = NHB: CSHAR (1.14)
|   |   |   |   |   NOWORKDAY = 1: CSHAR (38.16/10.89)
|   |   |   F_bs > 0: CSHAR (14.79/3.42)
CS_pass = 1: CSHAR (56.34/10.89)
```

Switching model from private car towards car sharing

Absolute values of attributes of the alternative and the base mode

The aim of the Decision Tree described in this section is to predict the switching intentions from private car towards car sharing in order to perform the same macro-trip in the future. Visual representations of the calibrated Decision Tree are reported in Appendix B.2.1 (Figure 51, which was divided into Figure 52, Figure 53, Figure 54, Figure 55 and Figure 56, for sake of readability), Table 43 report the corresponding textual description of the structure of the Tree. Observing Figure 51 (Figure 52, Figure 53, Figure 54, Figure 55 and Figure 56) one can note that owing a car sharing subscription is the most important factor that influences the adoption of car sharing (CS_pass), indicating that car sharers are satisfied with the service and are willing to use it in the future. Like in the previous Decision Tree, the number of employees in the household is the second most important variable (HH_work). If this number is null, the respondent is an unemployed or retired person. Following this branch of the Tree, persons without a driving licence (HH_driv is null) choose the base mode. Moreover, potential users are willing to switch to car sharing only if the walking time to reach the shared vehicle (CS_walk_dur) is less than 6 minutes, suggesting that increasing the capillarity of the service (e.g. by increasing the fleet size) is a key factor to promote the shift from private car. Like in the corresponding logit model, age plays a negative role, since only travellers aged 57 years or less are willing to adopt car sharing (AGE), indicating that this mode is not attractive for retired people, i.e. people more than 57 years old.

As regards households with employed people, negative switching intentions are predicted for macro-trips ending in a Limited Traffic Zone (LTZ), like in the logit model, highlighting that travellers are not aware of the free access to these areas for the shared cars. Following the branch relative to low household incomes (HH_inc), users are not willing to shift if the cost of car sharing is greater than 2.6 euros (CS_cost). Furthermore, potential switches are reported for individuals living alone who use car (F_car) and bike (F_bike) few times a week and never, respectively, suggesting that these persons might have low mobility needs. On the other hand, individuals living in households with more than one member, might potentially substitute private car both for systematic (HBW) and non-systematics (HBO) trips starting or ending at their home. Like in another branch of the Tree, the base alternative is chosen if the walking time to reach the shared vehicle (CS_walk_dur) is greater than 6 minutes, pointing out that this is a general threshold for car drivers. As expected, the availability of a reserved park near home (PARK_HOME) or near the working place (PARK_WORK) has a negative effect on switching intentions. Moreover, positive switches are predicted if the length of car sharing trip (CS_dist) is less than 14 kilometres, suggesting that this service can substitute the private car for urban trips. Furthermore, travellers are willing to use their car even if the walking duration to reach the vehicle (BASE_walk_dur) is positive, highlighting a general inertia to change their travel habits. Like in the corresponding logit model, household income plays a positive role, since users with very low income are less willing to switch to car sharing.

As regards individuals living in households with a high income level (HH_inc), owing a public transport pass (PT_pass) is a deterrent factor to switch to car sharing, suggesting that these two services are not considered complementary by car drivers. Like in another branch of the Tree, results indicate that car sharing can substitute car both for mandatory (HBW) and non-mandatory (HBO and NHO) purposes. As in the corresponding logit model, potential car sharing travellers are highly educated (EDU_LEVEL) and they frequently use active modes, such as bike (F_bike). In addition, positive switches are reported for distances lower than 6 kilometres (CS_dist), confirming that car sharing might substitute private car for short urban trips.

Table 43. Structure of the Decision tree for the switching intentions from car to car sharing

```
CS_pass = 0
|   HH_work <= 0
|   |   CS_walk_dur <= 6
|   |   |   AGE <= 57: CSHAR (10.2/1.92)
|   |   |   AGE > 57: BASE (122.74/33.11)
|   |   CS_walk_dur > 6: BASE (16.01)
|   HH_work > 0
|   |   LTZ = 0
|   |   |   HH_inc <= 2.75
|   |   |   |   CS_cost <= 2.6
|   |   |   |   |   HH_memb <= 1
|   |   |   |   |   |   F_car <= 2: CSHAR (10.57/0.64)
|   |   |   |   |   |   F_car > 2
|   |   |   |   |   |   |   F_bike <= 0
|   |   |   |   |   |   |   |   HH_inc <= 1.35: BASE (12.91/3.31)
|   |   |   |   |   |   |   |   HH_inc > 1.35: CSHAR (16.34/6.4)
|   |   |   |   |   |   |   F_bike > 0: CSHAR (13.51/1.92)
|   |   |   |   |   HH_memb > 1
|   |   |   |   |   |   HH_child <= 1
|   |   |   |   |   |   |   BASE_walk_dur <= 4
|   |   |   |   |   |   |   |   CS_walk_dur <= 6
|   |   |   |   |   |   |   |   |   OCC_LEV = WOOH
|   |   |   |   |   |   |   |   |   |   PARK_HOME = 1
|   |   |   |   |   |   |   |   |   |   |   F_car <= 2: CSHAR (28.08/11.52)
|   |   |   |   |   |   |   |   |   |   |   F_car > 2
|   |   |   |   |   |   |   |   |   |   |   |   BASE_walk_dur <= 0
|   |   |   |   |   |   |   |   |   |   |   |   |   CS_dist <= 14250
|   |   |   |   |   |   |   |   |   |   |   |   |   |   HH_child <= 0: BASE (32.45/13.25)
|   |   |   |   |   |   |   |   |   |   |   |   |   |   HH_child > 0: CSHAR (23.86/8.96)
|   |   |   |   |   |   |   |   |   |   |   |   |   CS_dist > 14250: BASE (11.52)
|   |   |   |   |   |   |   |   |   |   |   |   BASE_walk_dur > 0: BASE (76.63/13.25)
|   |   |   |   |   |   |   |   |   |   PARK_HOME = 0
|   |   |   |   |   |   |   |   |   |   |   CS_dur <= 11: BASE (12.01/4.97)
|   |   |   |   |   |   |   |   |   |   |   CS_dur > 11: CSHAR (16.45/3.2)
|   |   |   |   |   |   |   |   |   OCC_LEV = STN: BASE (11.63/3.31)
|   |   |   |   |   |   |   |   |   OCC_LEV = UNE: CSHAR (17.73/4.48)
|   |   |   |   |   |   |   |   |   OCC_LEV = RET: BASE (10.73/4.97)
|   |   |   |   |   |   |   |   |   OCC_LEV = WAH
|   |   |   |   |   |   |   |   |   |   F_car <= 2: BASE (15.1/1.66)
|   |   |   |   |   |   |   |   |   |   F_car > 2
|   |   |   |   |   |   |   |   |   |   |   HH_inc <= 1.9: BASE (13.29/4.97)
|   |   |   |   |   |   |   |   |   |   |   HH_inc > 1.9: CSHAR (14.15/2.56)
|   |   |   |   |   |   |   |   CS_walk_dur > 6: BASE (15.74/1.66)
|   |   |   |   |   |   |   BASE_walk_dur > 4
|   |   |   |   |   |   |   |   PARK_WORK = 0: CSHAR (51.41/16.65)
|   |   |   |   |   |   |   |   PARK_WORK = 1
|   |   |   |   |   |   |   |   |   CS_dur <= 27: CSHAR (15.06/5.12)
|   |   |   |   |   |   |   |   |   CS_dur > 27: BASE (12.91/3.31)
|   |   |   |   |   |   HH_child > 1
|   |   |   |   |   |   |   TRIP_PURP = HBW: CSHAR (23.22/8.32)
|   |   |   |   |   |   |   TRIP_PURP = HBO: CSHAR (21.3/6.4)
|   |   |   |   |   |   |   TRIP_PURP = NHO: BASE (3.84)
|   |   |   |   |   |   |   TRIP_PURP = NBEd: BASE (0.64)
|   |   |   |   |   |   |   TRIP_PURP = NHB: CSHAR (0.0)
|   |   |   |   CS_cost > 2.6: BASE (32.5/4.97)
|   |   |   HH_inc > 2.75
|   |   |   |   PT_pass = 0
|   |   |   |   |   TRIP_PURP = HBW
|   |   |   |   |   |   HH_driv <= 2
|   |   |   |   |   |   |   F_bike <= 0
|   |   |   |   |   |   |   |   BASE_walk_dur <= 0: CSHAR (55.21/12.16)
|   |   |   |   |   |   |   |   BASE_walk_dur > 0
|   |   |   |   |   |   |   |   |   CS_dist <= 5675: CSHAR (10.2/1.92)
|   |   |   |   |   |   |   |   |   CS_dist > 5675: BASE (12.27/3.31)
|   |   |   |   |   |   |   F_bike > 0: CSHAR (13.89/0.64)
```

```
|   |   |   |   |   |   HH_driv > 2
|   |   |   |   |   |   |   EDU_LEV = HS: BASE (15.48/3.31)
|   |   |   |   |   |   |   EDU_LEV = MP: CSHAR (18.63/7.04)
|   |   |   |   |   |   |   EDU_LEV = NHS: BASE (0.64)
|   |   |   |   |   TRIP_PURP = HBO: CSHAR (104.48/33.29)
|   |   |   |   |   TRIP_PURP = NHO: CSHAR (17.99/6.4)
|   |   |   |   |   TRIP_PURP = NBEd: BASE (4.48)
|   |   |   |   |   TRIP_PURP = NHB: BASE (1.28)
|   |   |   |   PT_pass = 1: BASE (11.63/3.31)
|   |   LTZ = 1: BASE (15.48/3.31)
CS_pass = 1: CSHAR (55.81/4.48)
```

Differences between attributes of the alternative and base mode

In this Decision Tree, differences between trip attributes of car sharing and private car are considered, in order to analyse how respondents compare these differences for the switching choices. Visual representations of the calibrated Decision Tree are reported in Appendix B.2.2 (

Figure 57, which was divided into Figure 58, Figure 59, Figure 60 and Figure 61, for sake of readability), whereas Table 44 report the structure of the Tree in a textual way. Observing

Figure 57 one can note that the Decision Tree is similar to the one with absolute values of trip attribute (Figure 47 and Table 42). In particular, car sharing members are more willing to adopt it in the future (CS_pass). Potential members have a high educational level (EDU_LEV). The use of bike has a positive effect (F_bike), whereas a high car frequency is often associated with non-switching intentions (F_car), highlighting the general inertia of car drivers to give up their private vehicle to shift to car sharing. Trips ending in Limited Traffic Zones (LTZ) are not likely to be replaced by car sharing. Moreover, car sharing might substitute car trips in non-working days (NOWORKDAY), and with both for mandatory and non-mandatory purposes (HBW, HBO and NHO).

In addition, this Decision Tree shows that car drivers are willing to switch to car sharing if they can reduce the walking time to reach the vehicle by at least 4 minutes (DELTA_walk_dur). Moreover, further positive shifts are predicted if the trip duration on car sharing is lower than the one on private car by at least 3 minutes (DELTA_dur). This analysis suggests that reducing the walking time to the shared vehicle and the travel time might be effective measures to promote the switch from private car.

Table 44. Structure of the Decision tree for the switching intentions from car to car sharing (relative values of trip attributes)

```
AGE <= 79
|   BASE_cost <= 0.02: BASE (30.96)
|   BASE_cost > 0.02
|   |   BASE_wait <= 3
|   |   |   F_bs <= 0
|   |   |   |   BASE_cost <= 1.2
|   |   |   |   |   BASE_dur <= 5: CSHAR (10.75)
|   |   |   |   |   BASE_dur > 5
|   |   |   |   |   |   HH_inc <= 1.9: BASE (29.82)
|   |   |   |   |   |   HH_inc > 1.9
|   |   |   |   |   |   |   BASE_cost <= 0.63: BASE (49.74/10.75)
|   |   |   |   |   |   |   BASE_cost > 0.63: CSHAR (34.12/12.61)
|   |   |   |   BASE_cost > 1.2: BASE (53.9)
|   |   |   F_bs > 0: CSHAR (11.9/1.15)
|   |   BASE_wait > 3
|   |   |   BASE_dist <= 18227
|   |   |   |   CS_walk_dur <= 20
|   |   |   |   |   HH_child <= 0
|   |   |   |   |   |   CS_pass = 0
|   |   |   |   |   |   |   PT_pass = 0
|   |   |   |   |   |   |   |   EDU_LEV = HS
|   |   |   |   |   |   |   |   |   NOWORKDAY = 0
|   |   |   |   |   |   |   |   |   |   OCC_LEV = WOOH: CSHAR (47.96/10.32)
|   |   |   |   |   |   |   |   |   |   OCC_LEV = STN: CSHAR (23.01/6.88)
|   |   |   |   |   |   |   |   |   |   OCC_LEV = UNE: CSHAR (17.63/6.88)
|   |   |   |   |   |   |   |   |   |   OCC_LEV = RET: BASE (24.51/10.75)
|   |   |   |   |   |   |   |   |   |   OCC_LEV = WAH: BASE (10.32)
|   |   |   |   |   |   |   |   |   NOWORKDAY = 1: CSHAR (35.7/3.44)
|   |   |   |   |   |   |   |   EDU_LEV = MP
|   |   |   |   |   |   |   |   |   LTZ = 0
|   |   |   |   |   |   |   |   |   |   GENDER = F: CSHAR (13.05/2.29)
|   |   |   |   |   |   |   |   |   |   GENDER = M: BASE (17.99/5.38)
|   |   |   |   |   |   |   |   |   LTZ = 1: CSHAR (11.9/1.15)
|   |   |   |   |   |   |   |   EDU_LEV = NHS
|   |   |   |   |   |   |   |   |   BASE_wait <= 6: CSHAR (34.12/12.61)
|   |   |   |   |   |   |   |   |   BASE_wait > 6: BASE (29.82)
|   |   |   |   |   |   |   PT_pass = 1
|   |   |   |   |   |   |   |   BASE_wait <= 25
|   |   |   |   |   |   |   |   |   HH_cars <= 0: BASE (17.2)
|   |   |   |   |   |   |   |   |   HH_cars > 0
|   |   |   |   |   |   |   |   |   |   BASE_cost <= 0.3: CSHAR (36.06/9.17)
|   |   |   |   |   |   |   |   |   |   BASE_cost > 0.3
|   |   |   |   |   |   |   |   |   |   |   HH_cars <= 1
|   |   |   |   |   |   |   |   |   |   |   |   PARK_HOME = 1
|   |   |   |   |   |   |   |   |   |   |   |   |   NOWORKDAY = 0
|   |   |   |   |   |   |   |   |   |   |   |   |   |   BASE_dist <= 2348: CSHAR (13.05/2.29)
|   |   |   |   |   |   |   |   |   |   |   |   |   |   BASE_dist > 2348: BASE (43.22/5.38)
|   |   |   |   |   |   |   |   |   |   |   |   |   NOWORKDAY = 1: CSHAR (37.2/10.32)
|   |   |   |   |   |   |   |   |   |   |   |   PARK_HOME = 0: BASE (10.32)
|   |   |   |   |   |   |   |   |   |   |   HH_cars > 1: BASE (41.28)
|   |   |   |   |   |   |   |   BASE_wait > 25: CSHAR (17.28/1.15)
|   |   |   |   |   |   CS_pass = 1: CSHAR (28.39/6.88)
|   |   |   |   |   HH_child > 0
|   |   |   |   |   |   F_bs <= 2
|   |   |   |   |   |   |   CS_cost <= 0.41: CSHAR (42.22/4.59)
|   |   |   |   |   |   |   CS_cost > 0.41
|   |   |   |   |   |   |   |   HH_memb <= 3: BASE (18.35)
|   |   |   |   |   |   |   |   HH_memb > 3
|   |   |   |   |   |   |   |   |   NOWORKDAY = 0: BASE (14.55/5.38)
|   |   |   |   |   |   |   |   |   NOWORKDAY = 1: CSHAR (22.65/1.15)
|   |   |   |   |   |   F_bs > 2: CSHAR (16.13)
|   |   |   |   CS_walk_dur > 20: CSHAR (30.32/3.44)
|   |   |   BASE_dist > 18227: CSHAR (86.74/11.47)
AGE > 79: BASE (37.84)
```

Switching model from public transport towards car sharing

Absolute values of attributes of the alternative and the base mode

In this section, results of the Decision Tree evaluating the switching intentions towards car sharing for public transport users are presented. Visual representations of the calibrated Decision Tree are reported in Appendix B.3.1 (Figure 62, which was divided into Figure 63, Figure 64 and Figure 65, for the sake of readability), whereas Table 45 reports the corresponding textual description. Unlike the previous logit model predicting the shift from public transport, in this Decision Tree, age (AGE) is the most important variable; in particular, the algorithm indicates that people aged 79 or more are not willing to switch. The second most important factor is the cost of the base alternative (BASE_cost); specifically, if the cost of public transport is very low, switching intentions are negative. These very low fares are associated with respondents owing a public transport subscription. As expected, the waiting time at the transit stop (BASE_wait) is significant; in particular, most of the positive switches (about 89%) are predicted if the waiting time is greater than 3 minutes, independently on the values of other variables. This suggests that a frequent public transport system with low waiting times might prevent switches towards car sharing. Moreover car sharing switches are often associated with high frequencies of bike sharing (F_bs), indicating that potential car sharers are familiar with sharing systems; a similar result was obtained in the corresponding logit model, where owing a bike sharing subscription had a positive effect on the swathing intention towards car sharing. Analogously, the Tree predicts positive switches if the macro-trip is performed in a non-working day (NOWORKDAY), suggesting that car sharing can substitute public transport during this period, since it might be less frequent. As regards weekdays, car sharing might be adopted by working people and students (OCC_LEV), indicating that the service can compete with public transport even for systematic purposes. Furthermore, respondents are more willing to adopt car sharing if the trip length (BASE_dist) is greater than 18 kilometres, indicating that car sharing could compete with sub urban public transport. For shorter distances, travellers might switch if the walking time to reach the shared vehicles (CS_walk_dur) is less than 20 minutes and the total fare (CS_cost) is lower than 0.4 euros, even if positive switches are reported also if the walking time is greater than 20 minutes. Like in previous models, being a car sharing member (CS_pass) foster users to adopt car sharing in the future. On the contrary, public transport subscribers might shift if the waiting time at the stop (BASE_wait) is greater than 25 minutes. Like in the logit models, females are more willing to switch (GENDER), rather than males, due to the privacy and safety provided by car sharing vehicles.

Table 45. Structure of the Decision tree for the switching intentions from public transport to car sharing

```
AGE <= 79
|   DELTA_wait <= -4
|   |   F_car <= 0.5
|   |   |   AGE <= 73
|   |   |   |   HH_child <= 1
|   |   |   |   |   F_pt <= 2
|   |   |   |   |   |   AGE <= 52
|   |   |   |   |   |   |   AGE <= 46: BASE (24.87/5.38)
|   |   |   |   |   |   |   AGE > 46: CSHAR (10.75)
|   |   |   |   |   |   AGE > 52: BASE (29.82)
|   |   |   |   |   F_pt > 2
|   |   |   |   |   |   PARK_WORK = 0
|   |   |   |   |   |   |   HH_inc <= 0.5: CSHAR (10.75)
|   |   |   |   |   |   |   HH_inc > 0.5
|   |   |   |   |   |   |   |   PT_pass = 0
|   |   |   |   |   |   |   |   |   TRIP_PURP = HBW: BASE (13.4/5.38)
|   |   |   |   |   |   |   |   |   TRIP_PURP = HBO
|   |   |   |   |   |   |   |   |   |   F_bike <= 0.5
|   |   |   |   |   |   |   |   |   |   |   OCC_LEV = WOOH: CSHAR (6.52/1.15)
|   |   |   |   |   |   |   |   |   |   |   OCC_LEV = STN: CSHAR (15.34/4.59)
|   |   |   |   |   |   |   |   |   |   |   OCC_LEV = UNE: CSHAR (10.75)
|   |   |   |   |   |   |   |   |   |   |   OCC_LEV = RET: CSHAR (20.72/4.59)
|   |   |   |   |   |   |   |   |   |   |   OCC_LEV = WAH: BASE (9.17)
|   |   |   |   |   |   |   |   |   |   F_bike > 0.5: CSHAR (10.75)
|   |   |   |   |   |   |   |   |   TRIP_PURP = NHO: BASE (1.15)
|   |   |   |   |   |   |   |   |   TRIP_PURP = NBEd: CSHAR (0.0)
|   |   |   |   |   |   |   |   |   TRIP_PURP = NHB: CSHAR (0.0)
|   |   |   |   |   |   |   |   PT_pass = 1
|   |   |   |   |   |   |   |   |   HH_inc <= 1.9: BASE (21.79)
|   |   |   |   |   |   |   |   |   HH_inc > 1.9
|   |   |   |   |   |   |   |   |   |   DELTA_wait <= -5
|   |   |   |   |   |   |   |   |   |   |   DELTA_cost <= 1.59914
|   |   |   |   |   |   |   |   |   |   |   |   DELTA_wait <= -25: CSHAR (11.9/1.15)
|   |   |   |   |   |   |   |   |   |   |   |   DELTA_wait > -25
|   |   |   |   |   |   |   |   |   |   |   |   |   HH_work <= 1: CSHAR (15.34/4.59)
|   |   |   |   |   |   |   |   |   |   |   |   |   HH_work > 1: BASE (24.08)
|   |   |   |   |   |   |   |   |   |   |   DELTA_cost > 1.59914: CSHAR (10.75)
|   |   |   |   |   |   |   |   |   |   DELTA_wait > -5: CSHAR (10.75)
|   |   |   |   |   |   PARK_WORK = 1: BASE (28.31/5.38)
|   |   |   |   HH_child > 1: CSHAR (20.72/4.59)
|   |   |   AGE > 73: BASE (25.23)
|   |   F_car > 0.5
|   |   |   GENDER = F
|   |   |   |   DELTA_cost <= -0.14: CSHAR (91.76/5.73)
|   |   |   |   DELTA_cost > -0.14
|   |   |   |   |   DELTA_walk_dur <= 5
|   |   |   |   |   |   DELTA_cost <= 1.3993
|   |   |   |   |   |   |   HH_inc <= 2.75
|   |   |   |   |   |   |   |   PARK_HOME = 1: CSHAR (118.56/21.79)
|   |   |   |   |   |   |   |   PARK_HOME = 0: BASE (16.84/5.38)
|   |   |   |   |   |   |   HH_inc > 2.75: BASE (19.14/5.38)
|   |   |   |   |   |   DELTA_cost > 1.3993: BASE (14.91)
|   |   |   |   |   DELTA_walk_dur > 5: CSHAR (16.13)
|   |   |   GENDER = M
|   |   |   |   LTZ = 0
|   |   |   |   |   DELTA_wait <= -14
|   |   |   |   |   |   TRIP_PURP = HBW: CSHAR (10.75)
|   |   |   |   |   |   TRIP_PURP = HBO: CSHAR (21.86/5.73)
|   |   |   |   |   |   TRIP_PURP = NHO: BASE (2.29)
|   |   |   |   |   |   TRIP_PURP = NBEd: CSHAR (0.0)
|   |   |   |   |   |   TRIP_PURP = NHB: CSHAR (0.0)
|   |   |   |   |   DELTA_wait > -14
|   |   |   |   |   |   DELTA_cost <= 0.003
|   |   |   |   |   |   |   AGE <= 39: BASE (13.76)
|   |   |   |   |   |   |   AGE > 39: CSHAR (47.17/14.91)
```

```
    |   |   |   |   |   |   DELTA_cost > 0.003: BASE (29.82)
    |   |   |   |   LTZ = 1: CSHAR (31.47/4.59)
    |   DELTA_wait > -4
    |   |   HH_work <= 0: BASE (45.87)
    |   |   HH_work > 0
    |   |   |   DELTA_cost <= 0.77
    |   |   |   |   DELTA_dur <= 6
    |   |   |   |   |   ORIG_TO = 1
    |   |   |   |   |   |   DELTA_wait <= -3: BASE (12.61)
    |   |   |   |   |   |   DELTA_wait > -3
    |   |   |   |   |   |   |   AGE <= 45
    |   |   |   |   |   |   |   |   HH_car_licence <= 0.5: CSHAR (19.93/9.17)
    |   |   |   |   |   |   |   |   HH_car_licence > 0.5: BASE (19.5)
    |   |   |   |   |   |   |   AGE > 45: CSHAR (20.72/4.59)
    |   |   |   |   |   ORIG_TO = 0: CSHAR (32.62/5.73)
    |   |   |   |   DELTA_dur > 6: BASE (14.91)
    |   |   |   DELTA_cost > 0.77: BASE (28.67)
    AGE > 79: BASE (37.84)
```

Differences between attributes of the alternative and base mode

In this version of the Decision Tree, differences between attributes of the macro-trip carried out on car sharing and public transport are considered as exogenous variables. The structure of the Decision Tree is shown in Appendix B.3.2 (Figure 66, which was divided into Figure 67, Figure 68, Figure 69, Figure 70, Figure 71, Figure 72 and Figure 73, for sake of readability), whereas a textual description is reported in Table 46. The final version of the Decision Tree is similar to the corresponding model where absolute values of trip attributes were adopted. In particular, age is the most important factor (AGE). Moreover, about 68% of the switches are predicted for car drivers (F_car), however, among less frequent drivers, about 91% of them tend to use frequently public transport. This suggests that potential members are either usual car drivers or frequent public transit users.

As regards trip attributes, the waiting time (DELTA_wait) is confirmed as the most important factor, like in the previous Decision Tree. In particular, about 87% of the positive switches are obtained when users can reduce their waiting time at the transit stop for at least 4 minutes; this confirms that interventions to reduce the waste of time at the stop might avoid the shift from public transport to car sharing. In case of a reduction of waiting time lower than 4 minutes, travellers are not willing to switch if the cost of car sharing (DELTA_cost) is greater than 0.8 euros or the related travel time (DELTA_dur) is more than 6 minutes longer, rather than public transport. On the other hand, if the reduction of waiting time is more than 4 minutes, potential travellers would pay more to perform the macro-trip on car sharing (DELTA_cost). Moreover, female potential users might pay up to 1.4 euros to avoid to wait at the transit stop, whereas males are not willing to pay more. This confirms that females are more likely to switch rather than males, like in the previous version of the model.

Table 46. Structure of the Decision tree for the switching intentions from public transport to car sharing (relative values of trip attributes)

```
AGE <= 79
|   DELTA_wait <= -4
|   |   F_car <= 0.5
|   |   |   AGE <= 73
|   |   |   |   HH_child <= 1
|   |   |   |   |   F_pt <= 2
|   |   |   |   |   |   AGE <= 52
|   |   |   |   |   |   |   AGE <= 46: BASE (24.87/5.38)
|   |   |   |   |   |   |   AGE > 46: CSHAR (10.75)
|   |   |   |   |   |   AGE > 52: BASE (29.82)
|   |   |   |   |   F_pt > 2
|   |   |   |   |   |   PARK_WORK = 0
|   |   |   |   |   |   |   HH_inc <= 0.5: CSHAR (10.75)
|   |   |   |   |   |   |   HH_inc > 0.5
|   |   |   |   |   |   |   |   PT_pass = 0
|   |   |   |   |   |   |   |   |   TRIP_PURP = HBW: BASE (13.4/5.38)
|   |   |   |   |   |   |   |   |   TRIP_PURP = HBO
|   |   |   |   |   |   |   |   |   |   F_bike <= 0.5
|   |   |   |   |   |   |   |   |   |   |   OCC_LEV = WOOH: CSHAR (6.52/1.15)
|   |   |   |   |   |   |   |   |   |   |   OCC_LEV = STN: CSHAR (15.34/4.59)
|   |   |   |   |   |   |   |   |   |   |   OCC_LEV = UNE: CSHAR (10.75)
|   |   |   |   |   |   |   |   |   |   |   OCC_LEV = RET: CSHAR (20.72/4.59)
|   |   |   |   |   |   |   |   |   |   |   OCC_LEV = WAH: BASE (9.17)
|   |   |   |   |   |   |   |   |   |   F_bike > 0.5: CSHAR (10.75)
|   |   |   |   |   |   |   |   |   TRIP_PURP = NHO: BASE (1.15)
|   |   |   |   |   |   |   |   |   TRIP_PURP = NBEd: CSHAR (0.0)
|   |   |   |   |   |   |   |   |   TRIP_PURP = NHB: CSHAR (0.0)
|   |   |   |   |   |   |   |   PT_pass = 1
|   |   |   |   |   |   |   |   |   HH_inc <= 1.9: BASE (21.79)
|   |   |   |   |   |   |   |   |   HH_inc > 1.9
|   |   |   |   |   |   |   |   |   |   DELTA_wait <= -5
|   |   |   |   |   |   |   |   |   |   |   DELTA_cost <= 1.59914
|   |   |   |   |   |   |   |   |   |   |   |   DELTA_wait <= -25: CSHAR (11.9/1.15)
|   |   |   |   |   |   |   |   |   |   |   |   DELTA_wait > -25
|   |   |   |   |   |   |   |   |   |   |   |   |   HH_work <= 1: CSHAR (15.34/4.59)
|   |   |   |   |   |   |   |   |   |   |   |   |   HH_work > 1: BASE (24.08)
|   |   |   |   |   |   |   |   |   |   |   DELTA_cost > 1.59914: CSHAR (10.75)
|   |   |   |   |   |   |   |   |   |   DELTA_wait > -5: CSHAR (10.75)
|   |   |   |   |   |   PARK_WORK = 1: BASE (28.31/5.38)
|   |   |   |   HH_child > 1: CSHAR (20.72/4.59)
|   |   |   AGE > 73: BASE (25.23)
|   |   F_car > 0.5
|   |   |   GENDER = F
|   |   |   |   DELTA_cost <= -0.14: CSHAR (91.76/5.73)
|   |   |   |   DELTA_cost > -0.14
|   |   |   |   |   DELTA_walk_dur <= 5
|   |   |   |   |   |   DELTA_cost <= 1.3993
|   |   |   |   |   |   |   HH_inc <= 2.75
|   |   |   |   |   |   |   |   PARK_HOME = 1: CSHAR (118.56/21.79)
|   |   |   |   |   |   |   |   PARK_HOME = 0: BASE (16.84/5.38)
|   |   |   |   |   |   |   HH_inc > 2.75: BASE (19.14/5.38)
|   |   |   |   |   |   DELTA_cost > 1.3993: BASE (14.91)
|   |   |   |   |   DELTA_walk_dur > 5: CSHAR (16.13)
|   |   |   GENDER = M
|   |   |   |   LTZ = 0
|   |   |   |   |   DELTA_wait <= -14
|   |   |   |   |   |   TRIP_PURP = HBW: CSHAR (10.75)
|   |   |   |   |   |   TRIP_PURP = HBO: CSHAR (21.86/5.73)
|   |   |   |   |   |   TRIP_PURP = NHO: BASE (2.29)
|   |   |   |   |   |   TRIP_PURP = NBEd: CSHAR (0.0)
|   |   |   |   |   |   TRIP_PURP = NHB: CSHAR (0.0)
|   |   |   |   |   DELTA_wait > -14
|   |   |   |   |   |   DELTA_cost <= 0.003
|   |   |   |   |   |   |   AGE <= 39: BASE (13.76)
```

```
|   |   |   |   |   |   |   AGE > 39: CSHAR (47.17/14.91)
|   |   |   |   |   |   DELTA_cost > 0.003: BASE (29.82)
|   |   |   |   LTZ = 1: CSHAR (31.47/4.59)
|   DELTA_wait > -4
|   |   HH_work <= 0: BASE (45.87)
|   |   HH_work > 0
|   |   |   DELTA_cost <= 0.77
|   |   |   |   DELTA_dur <= 6
|   |   |   |   |   ORIG_TO = 1
|   |   |   |   |   |   DELTA_wait <= -3: BASE (12.61)
|   |   |   |   |   |   DELTA_wait > -3
|   |   |   |   |   |   |   AGE <= 45
|   |   |   |   |   |   |   |   HH_car_licence <= 0.5: CSHAR (19.93/9.17)
|   |   |   |   |   |   |   |   HH_car_licence > 0.5: BASE (19.5)
|   |   |   |   |   |   |   AGE > 45: CSHAR (20.72/4.59)
|   |   |   |   |   ORIG_TO = 0: CSHAR (32.62/5.73)
|   |   |   |   DELTA_dur > 6: BASE (14.91)
|   |   |   DELTA_cost > 0.77: BASE (28.67)
AGE > 79: BASE (37.84)
```

Switching model from bike towards car sharing

Absolute values of attributes of the alternative and the base mode

The Decision Tree presented in this section aims to model the switch from bike to car sharing. Figure 74 (in Appendix B.4.1) and Table 47 report the structure of the Tree through a visual framework and a textual description, respectively. Observing Figure 74 (divided into Figure 75, Figure 76 and Figure 77, for sake of readability) one can note that car sharing cannot substitute the bike for short trips (CS_dist), in particular with a distance lower than 1.4 kilometres. Moreover, bikers are not willing to switch if the walking time to reach the shared car (CS_walk_dur) is greater than 9 minutes. Like in the corresponding logit model, household income (HH_inc) has a positive effect on the switching intentions, since travellers with low income are more willing to adopt bike. Unlike previous models, owing a car sharing subscription (CS_pass) has not a positive effect on the choice of car sharing, since negative shifts are obtained even for members of the service, however, there are many potential users who currently do not own a car sharing pass. Moreover, the gender of respondents (GENDER) has a significant effect; in particular, females are less willing to shift rather than males, since only 23% of positive switches are associated with female respondents. Moreover, male workers and students might adopt car sharing, whereas females are not willing to. Furthermore, as expected, many macro-trips on bike ending inside the city of Turin (DEST_TO) could be performed on car sharing, since the operative area, where shared vehicles can be returned, is within the boundaries of the city. Lastly, switches on bike are predicted for both working and non-working days (NOWORKDAY).

Table 47. Structure of the Decision tree for the switching intentions from bike to car sharing

```
CS_dist <= 1434: BASE (94.34)
CS_dist > 1434
|   CS_walk_dur <= 9
|   |   HH_inc <= 1.1: BASE (28.3)
|   |   HH_inc > 1.1
|   |   |   CS_pass = 0
|   |   |   |   CS_walk_dur <= 6
|   |   |   |   |   GENDER = F
|   |   |   |   |   |   EDU_LEV = HS
|   |   |   |   |   |   |   NOWORKDAY = 0
|   |   |   |   |   |   |   |   OCC_LEV = WOOH: BASE (62.74/25.0)
|   |   |   |   |   |   |   |   OCC_LEV = STN: BASE (9.43)
|   |   |   |   |   |   |   |   OCC_LEV = UNE: CSHAR (43.87/18.87)
|   |   |   |   |   |   |   |   OCC_LEV = RET: BASE (0.0)
|   |   |   |   |   |   |   |   OCC_LEV = WAH: BASE (28.3)
|   |   |   |   |   |   |   NOWORKDAY = 1: BASE (28.3)
|   |   |   |   |   |   EDU_LEV = MP
|   |   |   |   |   |   |   NOWORKDAY = 0
|   |   |   |   |   |   |   |   ORIG_TO = 1: BASE (28.3)
|   |   |   |   |   |   |   |   ORIG_TO = 0: CSHAR (25.0)
|   |   |   |   |   |   |   NOWORKDAY = 1: CSHAR (25.0)
|   |   |   |   |   |   EDU_LEV = NHS: CSHAR (25.0)
|   |   |   |   |   GENDER = M
|   |   |   |   |   |   EDU_LEV = HS
|   |   |   |   |   |   |   DEST_TO = 1: CSHAR (281.6/56.6)
|   |   |   |   |   |   |   DEST_TO = 0
|   |   |   |   |   |   |   |   TRIP_PURP = HBW: CSHAR (25.0)
|   |   |   |   |   |   |   |   TRIP_PURP = HBO: BASE (18.87)
|   |   |   |   |   |   |   |   TRIP_PURP = NHO: CSHAR (0.0)
|   |   |   |   |   |   |   |   TRIP_PURP = NBEd: CSHAR (0.0)
|   |   |   |   |   |   |   |   TRIP_PURP = NHB: CSHAR (0.0)
|   |   |   |   |   |   EDU_LEV = MP
|   |   |   |   |   |   |   OCC_LEV = WOOH: CSHAR (34.43/9.43)
|   |   |   |   |   |   |   OCC_LEV = STN: CSHAR (25.0)
|   |   |   |   |   |   |   OCC_LEV = UNE: CSHAR (34.43/9.43)
|   |   |   |   |   |   |   OCC_LEV = RET: BASE (9.43)
|   |   |   |   |   |   |   OCC_LEV = WAH: CSHAR (0.0)
|   |   |   |   |   |   EDU_LEV = NHS: BASE (28.3)
|   |   |   |   CS_walk_dur > 6: CSHAR (50.0)
|   |   |   CS_pass = 1: BASE (18.87)
|   CS_walk_dur > 9: BASE (75.47)
```

Differences between attributes of the alternative and base mode

Visual representations of the calibrated Decision Tree are reported in Appendix B.4.2 (Figure 78 , which was divided into Figure 79, Figure 80 and Figure 81, for sake of readability). Decision Tree considers the difference of trip attributes between car sharing and bike. Table 48 reports the corresponding textual description. The Decision Tree depicted in Figure 78 is similar to the previous one. Negative switching intentions are predicted even if travellers can reduce the travel time by at least 27 minutes (DELTA_dur), by taking shared cars instead of bike. Like in the previous model, being a member of car sharing (CS_pass) has a negative effect on the switch; whereas, like in the logit model, owing a public transport pass generates positive switches. Moreover, car sharing might substitute bike for trips performed both in working days (NOWORKDAY), with working purposes (HBW), and in non-working days, particularly if carried out by students (OCC_LEV).

Furthermore, potential car sharers are willing to pay up to about 0.3 euros to shift (DELTA_cost). In addition, travellers might give up bike if they can reduce the walking time to reach the vehicle by at least 5 minutes (DELTA_walk_dur).

Table 48. Structure of the Decision tree for the switching intentions from bike to car sharing (relative values of trip attributes)

```
DELTA_dur <= -27: BASE (66.04)
DELTA_dur > -27
|   DELTA_cost <= 0.26: BASE (47.17)
|   DELTA_cost > 0.26
|   |   CS_pass = 0
|   |   |   DELTA_walk_dur <= -5: CSHAR (50.0)
|   |   |   DELTA_walk_dur > -5
|   |   |   |   DELTA_dist <= -25: CSHAR (50.0)
|   |   |   |   DELTA_dist > -25
|   |   |   |   |   AGE <= 19: BASE (66.04)
|   |   |   |   |   AGE > 19
|   |   |   |   |   |   GENDER = F
|   |   |   |   |   |   |   PT_pass = 0
|   |   |   |   |   |   |   |   EDU_LEV = HS: BASE (157.08/25.0)
|   |   |   |   |   |   |   |   EDU_LEV = MP
|   |   |   |   |   |   |   |   |   NOWORKDAY = 0
|   |   |   |   |   |   |   |   |   |   ORIG_TO = 1: BASE (37.74)
|   |   |   |   |   |   |   |   |   |   ORIG_TO = 0: CSHAR (25.0)
|   |   |   |   |   |   |   |   |   NOWORKDAY = 1: CSHAR (25.0)
|   |   |   |   |   |   |   |   EDU_LEV = NHS: BASE (9.43)
|   |   |   |   |   |   |   PT_pass = 1: CSHAR (25.0)
|   |   |   |   |   |   GENDER = M
|   |   |   |   |   |   |   NOWORKDAY = 0
|   |   |   |   |   |   |   |   TRIP_PURP = HBW: CSHAR (59.43/9.43)
|   |   |   |   |   |   |   |   TRIP_PURP = HBO
|   |   |   |   |   |   |   |   |   DEST_TO = 1: CSHAR (218.87/18.87)
|   |   |   |   |   |   |   |   |   DEST_TO = 0: BASE (18.87)
|   |   |   |   |   |   |   |   TRIP_PURP = NHO: BASE (53.3/25.0)
|   |   |   |   |   |   |   |   TRIP_PURP = NBEd: CSHAR (0.0)
|   |   |   |   |   |   |   |   TRIP_PURP = NHB: CSHAR (0.0)
|   |   |   |   |   |   |   NOWORKDAY = 1
|   |   |   |   |   |   |   |   OCC_LEV = WOOH: BASE (18.87)
|   |   |   |   |   |   |   |   OCC_LEV = STN: CSHAR (43.87/18.87)
|   |   |   |   |   |   |   |   OCC_LEV = UNE: BASE (0.0)
|   |   |   |   |   |   |   |   OCC_LEV = RET: BASE (9.43)
|   |   |   |   |   |   |   |   OCC_LEV = WAH: BASE (0.0)
|   |   CS_pass = 1: BASE (18.87)
```

Switching model from walking towards car sharing

Absolute values of attributes of the alternative and the base mode

The aim of this Decision Tree is to analyse the switch from walking towards car sharing. Visual representations of the calibrated Decision Tree are shown in Appendix B.5.1 (Figure 82, which was divided into Figure 83 and Figure 84, for the sake of readability) and Table 49 reports the corresponding textual description. The estimated Decision Tree shows that the number of household members (HH_memb) is the most important variable, indicating that individuals living alone are not willing to adopt car sharing. Moreover, the second most important factor affecting the decision to shift is the length of the macro-trip on foot (BASE_dist); in particular, trips shorter than about 300 meters are not likely to be replaced by car sharing. In addition, switches to car sharing are predicted if the trip duration (BASE_dur) is greater than about 30 minutes. This highlights that short trips are not suitable for car sharing, as expected. Unlike the corresponding logit model, age (AGE) has a significant effect, since most of the respondents switching to car sharing are aged less than 60 years (about 86%). Moreover, potential car sharing users use also bike sharing (F_bs), and they own a public transport subscription (PT_pass), suggesting that they are more familiar with shared systems (in which the vehicle or the trip is shared with other persons), rather than with private vehicles. Furthermore, if the macro-trip is performed in non-working days (NOWORKDAY), travellers tend not to shift, suggesting that car sharing is more likely to substitute walking trips with systematic purposes; this observation is confirmed by the positive effect, on the switching intention, of home based work trip (HBW) and of being a worker (WOOH). In addition, like in previous Decision Trees, income (HH_inc) has a positive effect on the decision to adopt car sharing, since most of the positive switches (about 64%) are reported for a monthly income greater than 1650 euros.

Table 49. Structure of the Decision tree for the switching intentions from walking to car sharing

```
HH_memb <= 1: BASE (77.15)
HH_memb > 1
|   BASE_dist <= 228: BASE (35.61)
|   BASE_dist > 228
|   |   AGE <= 60
|   |   |   AGE <= 24
|   |   |   |   HH_driv <= 1: CSHAR (20.71/1.48)
|   |   |   |   HH_driv > 1: BASE (53.41)
|   |   |   AGE > 24
|   |   |   |   F_bs <= 0
|   |   |   |   |   HH_inc <= 1.65
|   |   |   |   |   |   CS_cost <= 1.4: BASE (37.09)
|   |   |   |   |   |   CS_cost > 1.4: CSHAR (20.71/1.48)
|   |   |   |   |   HH_inc > 1.65
|   |   |   |   |   |   BASE_dur <= 27
|   |   |   |   |   |   |   CS_dur <= 11
|   |   |   |   |   |   |   |   NOWORKDAY = 0
|   |   |   |   |   |   |   |   |   HH_cars <= 1
|   |   |   |   |   |   |   |   |   |   HH_memb <= 3
|   |   |   |   |   |   |   |   |   |   |   OCC_LEV = WOOH: CSHAR (128.74/13.35)
|   |   |   |   |   |   |   |   |   |   |   OCC_LEV = STN: CSHAR (0.0)
|   |   |   |   |   |   |   |   |   |   |   OCC_LEV = UNE: BASE (5.93)
|   |   |   |   |   |   |   |   |   |   |   OCC_LEV = RET: BASE (1.48)
|   |   |   |   |   |   |   |   |   |   |   OCC_LEV = WAH: CSHAR (25.17/5.93)
|   |   |   |   |   |   |   |   |   |   HH_memb > 3: CSHAR (38.46)
|   |   |   |   |   |   |   |   |   HH_cars > 1
|   |   |   |   |   |   |   |   |   |   PT_pass = 0: BASE (54.9)
|   |   |   |   |   |   |   |   |   |   PT_pass = 1: CSHAR (25.17/5.93)
|   |   |   |   |   |   |   |   NOWORKDAY = 1: BASE (35.61)
|   |   |   |   |   |   |   CS_dur > 11
|   |   |   |   |   |   |   |   TRIP_PURP = HBW: CSHAR (60.66/2.97)
|   |   |   |   |   |   |   |   TRIP_PURP = HBO: CSHAR (20.71/1.48)
|   |   |   |   |   |   |   |   TRIP_PURP = NHO: BASE (2.97)
|   |   |   |   |   |   |   |   TRIP_PURP = NBEd: CSHAR (0.0)
|   |   |   |   |   |   |   |   TRIP_PURP = NHB: CSHAR (0.0)
|   |   |   |   |   |   BASE_dur > 27: CSHAR (100.6/4.45)
|   |   |   |   F_bs > 0: CSHAR (57.69)
|   |   AGE > 60
|   |   |   CS_cost <= 1.8
|   |   |   |   CS_cost <= 0.21
|   |   |   |   |   ORIG_TO = 1: CSHAR (26.65/7.42)
|   |   |   |   |   ORIG_TO = 0: BASE (13.35)
|   |   |   |   CS_cost > 0.21: BASE (129.08)
|   |   |   CS_cost > 1.8: CSHAR (28.13/8.9)
```

Differences between attributes of the alternative and base mode

In this Decision Tree, differences between the characteristics of the macro-trip performed by car sharing and on foot are considered as exogenous variables, instead of absolute values. Visual representations of the calibrated Decision Tree are reported in Appendix B.5.2 (Figure 85, which was divided into Figure 86, Figure 87 and Figure 88, for the sake of readability), whereas Table 50 reports the textual description of the Tree. Observing Figure 85 (Figure 86, Figure 87 and Figure 88) one can note that the framework is similar to the previous specification of the model. In particular, both household members (HH_memb) and age of the individual (AGE) are significant factors affecting the switching decision. Moreover, as in the previous model, positive switches are predicted for working people (OCC_LEV). However, users are willing to shift to car sharing if the macro-trip is performed in non-working days (NOWORKDAY) or, in weekdays for non-systematic purposes (TRIP_PURP equal to HBO and NHO), unlike in the previous model. As regards attributes of the macro-trip, people aged more than 60 years are willing to pay more to adopt car sharing (DELTA_cost), in particular, they would pay more than 1.8 euros, whereas younger people would pay no more than 0.78 euros.

Table 50. Structure of the Decision tree for the switching intentions from walking to car sharing (relative values of trip attributes)

```
HH_memb <= 1: BASE (77.15)
HH_memb > 1
|   AGE <= 60
|   |   DELTA_dur <= -39
|   |   |   TRIP_PURP = HBW: CSHAR (19.23)
|   |   |   TRIP_PURP = HBO: CSHAR (96.15)
|   |   |   TRIP_PURP = NHO: BASE (4.45)
|   |   |   TRIP_PURP = NBEd: BASE (1.48)
|   |   |   TRIP_PURP = NHB: CSHAR (0.0)
|   |   DELTA_dur > -39
|   |   |   PT_pass = 0
|   |   |   |   HH_inc <= 1.65: BASE (48.96)
|   |   |   |   HH_inc > 1.65
|   |   |   |   |   AGE <= 24: BASE (35.61)
|   |   |   |   |   AGE > 24
|   |   |   |   |   |   DELTA_cost <= 0.29: BASE (28.19)
|   |   |   |   |   |   DELTA_cost > 0.29
|   |   |   |   |   |   |   DELTA_dist <= 1026
|   |   |   |   |   |   |   |   F_bike <= 2
|   |   |   |   |   |   |   |   |   DELTA_cost <= 0.78
|   |   |   |   |   |   |   |   |   |   AGE <= 34
|   |   |   |   |   |   |   |   |   |   |   OCC_LEV = WOOH
|   |   |   |   |   |   |   |   |   |   |   |   NOWORKDAY = 0
|   |   |   |   |   |   |   |   |   |   |   |   |   TRIP_PURP = HBW: BASE (2.97)
|   |   |   |   |   |   |   |   |   |   |   |   |   TRIP_PURP = HBO: CSHAR (62.14/4.45)
|   |   |   |   |   |   |   |   |   |   |   |   |   TRIP_PURP = NHO: CSHAR (20.71/1.48)
|   |   |   |   |   |   |   |   |   |   |   |   |   TRIP_PURP = NBEd: BASE (1.48)
|   |   |   |   |   |   |   |   |   |   |   |   |   TRIP_PURP = NHB: CSHAR (0.0)
|   |   |   |   |   |   |   |   |   |   |   |   NOWORKDAY = 1: CSHAR (19.23)
|   |   |   |   |   |   |   |   |   |   |   OCC_LEV = STN: CSHAR (0.0)
|   |   |   |   |   |   |   |   |   |   |   OCC_LEV = UNE: BASE (2.97)
|   |   |   |   |   |   |   |   |   |   |   OCC_LEV = RET: CSHAR (0.0)
|   |   |   |   |   |   |   |   |   |   |   OCC_LEV = WAH: CSHAR (19.23)
|   |   |   |   |   |   |   |   |   |   AGE > 34
|   |   |   |   |   |   |   |   |   |   |   F_pt <= 0.5: BASE (26.71)
|   |   |   |   |   |   |   |   |   |   |   F_pt > 0.5
|   |   |   |   |   |   |   |   |   |   |   |   NOWORKDAY = 0
|   |   |   |   |   |   |   |   |   |   |   |   |   EDU_LEV = HS: BASE (10.39)
|   |   |   |   |   |   |   |   |   |   |   |   |   EDU_LEV = MP: CSHAR (25.17/5.93)
|   |   |   |   |   |   |   |   |   |   |   |   |   EDU_LEV = NHS: CSHAR (0.0)
|   |   |   |   |   |   |   |   |   |   |   |   NOWORKDAY = 1: CSHAR (20.71/1.48)
|   |   |   |   |   |   |   |   |   DELTA_cost > 0.78: BASE (25.22)
|   |   |   |   |   |   |   |   F_bike > 2: CSHAR (38.46)
|   |   |   |   |   |   |   DELTA_dist > 1026: BASE (14.84)
|   |   |   PT_pass = 1
|   |   |   |   AGE <= 35
|   |   |   |   |   NOWORKDAY = 0: BASE (19.29)
|   |   |   |   |   NOWORKDAY = 1: CSHAR (23.68/4.45)
|   |   |   |   AGE > 35
|   |   |   |   |   OCC_LEV = WOOH: CSHAR (103.57/7.42)
|   |   |   |   |   OCC_LEV = STN: CSHAR (0.0)
|   |   |   |   |   OCC_LEV = UNE: CSHAR (20.71/1.48)
|   |   |   |   |   OCC_LEV = RET: CSHAR (19.23)
|   |   |   |   |   OCC_LEV = WAH: BASE (5.93)
|   AGE > 60
|   |   DELTA_cost <= 1.8
|   |   |   DELTA_cost <= 0.21
|   |   |   |   EDU_LEV = HS: CSHAR (26.65/7.42)
|   |   |   |   EDU_LEV = MP: BASE (2.97)
|   |   |   |   EDU_LEV = NHS: BASE (11.87)
|   |   |   DELTA_cost > 0.21: BASE (136.5)
|   |   DELTA_cost > 1.8: CSHAR (28.13/8.9)
```

Analysis of results of Decision Trees

This section summarizes the results obtained from the previously reported Decision Trees; each of them predicts the switching intentions from the travel mode currently adopted to perform the macro-trip towards car sharing. In all models, except the switching model of bikers, car sharing members are more willing to adopt shared vehicles in the future, replacing the reported mode used to carry out the macro-trip. This indicates that members are satisfied with the current service.

Car drivers tend to show a high inertia to give up their private vehicles. However, potential car sharing users are not old, they have a high level of education and they frequently use active modes, such as bike. Furthermore, the model indicates that car sharing can potentially substitute short urban trips (up to 14 kilometres), performed both for systematic and non-systematic purposes. The analysis suggests that two measures might be effective to induce the shift from private car. The first one is to reduce the walking time to reach the shared vehicle; in particular, travellers might switch if the walking time is lower than 4 minutes, respect to the walking time to reach their private car, and, in any case, they are willing to walk for 6 minutes, at maximum. Therefore, interventions to decrease walking time should be carried out, such as increasing the capillarity of the system (e.g. by increasing the fleet size) or through a proper vehicles relocation, which would allow individuals to find available shared cars wherever and whenever they need them. The second effective measure is to reduce the duration of the trip on car sharing by at least 3 minutes. Such interventions include, for example, giving free access to public transport reserved lanes, in order to avoid traffic congestion, or allowing free access to central zones, in order to take shorter paths, by crossing the city centre. On the other hand, allowing free access to Limited Traffic Zones vehicles is not found to be a proper action to promote the switch.

Public transport users who reported positive switching intentions are not old and they are familiar with sharing systems, such as bike sharing. Furthermore, potential member are either frequent car drivers or frequent public transport users. Moreover, females tend to be more willing to shift to car sharing rather than males. This might be due to the higher privacy and safety provided by car sharing vehicles, respect to public transit, where users have to share the travel mean with other passengers. Car sharing might substitute public transport both in non-working days and in weekdays, in particular if the trip is carried out by employees or students, suggesting that the service can satisfy both systematic and non-systematic activities. The analysis indicates that car sharing can compete with sub urban public transport, i.e. for trips longer than 18 kilometres. Positive switches are predicted for non-working days, when the public transport service is typically less frequent. In addition, travellers are willing to switch to car sharing if they can reduce their waiting time at the transit stop. In particular, potential members might switch if they have to wait for more than 3 minutes, moreover results show that they are willing to pay up to 0.8 euros more than the public transport fare to reduce the waiting time by 4 minutes. Furthermore, females might pay more rather than males to avoid waiting at the stop. This indicates that increasing the frequency of public transport service to decrease the waiting time at the transit stops is a key intervention to prevent the switch towards car sharing. Moreover, the analysis of results highlights that users might not adopt car sharing if public transport fares are very low. Lastly, travellers might not shift if the duration of the trip on car sharing is greater; this points out that increasing the commercial speed of public transport system might reduce switches towards car sharing, for example by creating reserved public transport lanes or a traffic light priority system.

Potential car sharing users, who adopted bike to perform the macro-trip, tend to be males, living in households with a high income level. Car sharing might compete with bike for trips carried out by students, in non-working days, or for working purposes, in weekdays. However, short trips cannot be substituted by car sharing, in particular, trips shorter than 1.4 kilometres. Moreover, users might shift if they can reduce the walking time to reach the travel means by at least 5 minutes, even if they are not willing to walk for more than 9 minutes. The analysis highlights that interventions to reduce walking time to reach the shared vehicle might induce a shift from bike to car sharing.

As regards walking trips, potential members are not old, they live in non-single households and they are familiar with sharing and public transport systems. Moreover, car sharing seems to compete with walking for systematic purposes. On the other hand, car sharing cannot substitute walking for short trips, in particular for trips shorter than 300 meters; on the contrary, positive switches are predicted if the walking time is greater than 30 minutes.

5.3.4. Visual approach

Introduction

In this section, a visual and descriptive approach is adopted in order to visualize the domain of traditional travel modes and car sharing. Following this method, the combined effect of selected trip characteristics on the choice of each mode is represented through visual charts. Data visualization is an effective way to represent complex and large datasets, obtaining an accessible and easily understandable summary of results (Yu and He, 2017).

Visual techniques in transportation studies were previously used for several aims. First, heat maps were adopted to evaluate spatial relationships among variables. Essa et al. adopted heat maps to compare real and simulated results of conflicts locations along many road sections (Essa and Sayed, 2015). Similarly, Wang et al. used heat maps to better understand the changes in the number of conflicts at different locations in a bus stop area (Wang et al., 2018). Moreover, in a pedestrian environment, Li et al. combined heat and real maps in order to visualize areas with different Level Of Service (Li et al., 2019). Secondly, heat maps were used to represent complex spatiotemporal interactions, in particular, to estimate traffic conditions on roads. Yildirimoglu and Geroliminis reported travel speed registered by loop detectors in spatial-temporal heat maps, in order to identify bottlenecks and congested road sections (Yildirimoglu and Geroliminis, 2013). Likewise, Ahn et al. define three-dimensional heat maps to visualize traffic conditions on roads, in particular to represent the correlation among space, time and traffic flow (Ahn et al., 2014). Heat maps were also introduced to visualize dynamic changes of some measures used in transport analysis. Stipancic et al. adopted heat maps in order to represent aggregate values of a proposed congestion index (Stipancic et al., 2017). Hu et al. visualized space-time job accessibility patterns using three-dimensional heat maps (Hu and Downs, 2019). Yang et al. adopted density maps to obtain spatiotemporal information about taxicab availabilities and travellers' activities (Yang et al., 2017). Glick and Figliozzi used heat maps to represent transit performance measures and to identify critical cases (Glick and Figliozzi, 2017).

In addition to visualization purposes, heat maps were generated as the basis to apply several statistical and mathematical techniques to derive further information. Nguyen et al. applied clustering analysis on previously generated heat maps in order to extract and classify highway traffic congestion patterns (Nguyen et al., 2019). Starting from heat maps, representing spatiotemporal characteristics of bus travel demand, Yu and He proposed an approach, based on Principal Component Analysis and clustering, to identify the distribution patterns of transit demand (Yu and He, 2017).

However, there are no previous works adopting a visual approach in mode choice analysis. The proposed methodology, unlike classical mode choice models, does not need any statistical hypothesis about input data, therefore it can be applied to any dataset, without high computational effort. Furthermore, this approach allows analysing the combined and non-linear effect of multiple trip attributes, complementing quantitative analysis developed with mode choice models. Results thus obtained are significant for the study of the best ambit of use of different transport modes, in order to understand which kinds of trips are more conducive to be performed by car sharing. To reach this aim two kinds of visualization charts were generated: modal switch heat maps and modal switch density maps. The methods used to build these maps are described in the following.

Modal switch heat maps

To derive the charts of the first kind, two attributes of the macro-trip, namely total travel time and total travel distance, are respectively discretized into n travel time bins whose fixed range is 5 minutes and m travel distance bins whose fixed range is 2 kilometres. The total travel time was computed as the sum of in-vehicle, waiting and walking time. All trip chains having the same combination of travel time and travel distance bin are then jointly considered in a unique set, irrespective of the travel means that was used, and therefore $n * m$ different sets are generated.

Four heat maps of this first kind were derived, where each map shows the fraction of respondents willing to shift to one of the four switching modes presented in the Stated-preferences choice tasks (private car, public transport, bike and car sharing) (see appendix A for further details on Stated-preference experiments), for all sets that contain at least 10 trips. Three additional heat maps of the second kind were derived, where total travel time and total travel cost were rather considered, thus excluding the bike switching mode which has no associated cost. The range of cost bins is fixed at 0.5 euros.

Different sizes of bins for both kinds of heat maps were evaluated. Clearly, the larger the size the larger is the number of observations there contained and therefore related results are more reliable. On the other hand, too large bins are originating oversimplified plots that might lead to poor interpretation. The final size of the bins was set in order to strike the right balance between these two contrasting factors. Consequently, heat maps thus generated can be easily read showing enough and reliable information about trip characteristics.

Cold regions in all maps show characteristics of the chained trip that are associated with lower mode shift propensities, while hot regions point out larger shifting propensities. Clearly, the shifting propensity is directly affected by the Stated-preferences attributes levels, but here the focus is not on comparing the used mode and the shifting mode, which was rather done in a previous section. The main interest of these heat maps rather lies in comparing charts for different travel modes. This leads to a visualization of the preferred ambits of use of each switching mode, particularly in case traditional travel modes (car, public transport and bike) and car sharing are considered.

Modal switch density maps

As a complement to the above representations, a second group of charts were created in order to better understand the relationship between a switching mode and the current one (declared in the Revealed-preferences part of the survey). In particular, first, only chained trips with positive values of switch were considered. The same attributes of the above mentioned second kind of heat maps are considered here, namely travel times and travel costs. However, in this case, the differences between Stated-preferences attributes of the alternative mode and the corresponding attributes of the current mode were computed for each chained trip and grouped into pre-determined bins. Each bin is therefore containing those trips that could be performed with the switching mode in the future. The corresponding cardinality is plotted in a graph on a grey scale, where the darker colour represents a larger number of trips.

Then the same procedure was repeated for trips with negative switching intentions. Therefore two graphs were generated for each couple of switching mode and the current one. In particular, the first group of graphs plots positive switching intention answers and the second one plots negative switching intention answers. Positive values on the horizontal and vertical axis respectively mean larger travel times and larger travel costs for Stated-preferences modes over current modes, therefore making the switching option not convenient. Thus, in each of the four quadrants of the graphs, either the switching mode or the current one is advantageous for one or both of the two Stated-preferences attributes. The bike mode was not considered since the associated trip cost is null.

Adopting this graphical approach rather than using a mode choice model with the same variables, allows obtaining more qualitative but rich information. Even if the proposed visual approach does not provide classical parameters derived through an econometric approach, such as the Value Of Time and demand elasticities, it allows to immediately understand the combined and non-linear effect of two variables on the choice of each of the four switching modes. Identifying non-linear trends in variables is useful to introduce these effects in mode choice models (Pinjari and Bhat, 2006). Therefore this method can complement more quantitative analyses, which were previously described.

Analysis of results of the visual approach

Observing the cold areas of Figure 26 and Figure 27 one can note that the switching intention percentage towards car sharing is generally low, compared to the one towards car (Figure 28 and Figure 29) and public transport (Figure 30 and Figure 31), possibly because of its relatively recent introduction in the study area. In particular, even if in Turin the number of vehicles of car sharing operators is quite high with about 8 cars per square kilometre (Ciuffini et al., 2018), Figure 26 and Figure 27 confirm that the knowledge of car sharing system is not common among Turin inhabitants. In the graphs plotting distance versus time, the slope of a hypothetical straight line passing through the origin is the velocity of the reported trip chain. Therefore, Figure 28 shows that the majority of people choose the car for quicker trips, whereas the choice to switch towards car sharing seems to be less dependent on the speed of the trip (Figure 26). This might in part point to the current limitations of car sharing systems on the spatial localization of trip origins and destinations related to their service operational area, which make them a less viable option for trips in suburban areas whose speed is generally higher. Even if the Stated-preferences experiment did not make specific reference to the service area limitation of current services, it is likely that respondents have considered the characteristics of the existing car sharing offer in Turin.

Furthermore, the comparison among Figure 26, Figure 28 and Figure 30 indicates that car, car sharing and public transport are not suitable for short trips (up to 2 kilometres) with long duration (up to 30 minutes), since these trips are usually performed walking or by bike. Moreover car and car sharing are not chosen for trips shorter than 10 kilometres and lasting around 60 minutes (Figure 26 and Figure 28); however this kind of trips might be performed on public transport (Figure 30). Those trips might be performed by “transit captives”, or in general by people that are reluctant in using either cars or car sharing.

The distribution of hot areas of costs of car (Figure 29), car sharing (Figure 27) and public transport (Figure 31), suggests that public transport prospective users are willing to accept more travel time in order to save money. Furthermore, in these graphs the slope of a hypothetical straight line passing through the origin represents a sort of value of time. Therefore one can note that the highest value is reported for car, a medium value for car sharing and the lowest for public transport, as expected. From this visual analysis, car sharing is found to be a mix of car and public transport.

Observing Figure 26, Figure 28 and Figure 30, it is possible to overlap the areas with the highest values of switching intention percentages for each modal switch heat map of motorised travel modes, which represent the best ambit of use of each of them. Following this virtual procedure, the car sharing area lies in the intersection between car and public transport covering trips with short distances and times, which are typical of an urban contest.

Coming to the consideration of density maps, Figure 32 and Figure 34 were analysed. In the first quadrant (north-east), the majority of points have a negative switch, as expected (Figure 34), since the current mode car is more advantageous than car sharing in terms of both time and cost. However, there are some points with a positive value of switch and, in particular, only 8% of these respondents have a car sharing subscription. This suggests that this mode might attract some people even if it is disadvantageous on travel time and travel cost grounds. On the other hand, comparing the third quadrant (south-west) of both figures shows that the majority of points have negative values of switch (Figure 34), even if car sharing trips are both shorter and cheaper than car trips. Therefore, reducing the cost and the duration of trips on car sharing does not seem to be the main way to attract the majority of people away from private cars to achieve a radical overhaul of mode shares. This suggests that subjective determinants of the use of private car rather than car sharing currently exist. In the north-west quadrant there are more non-switch (Figure 34) than switch (Figure 32) points, while the opposite is found in the south-west quadrant. The overall conclusion is that car sharing should be more competitive on cost rather than on travel time grounds to lure people away from their cars, as also found when considering the above introduced mode switch models.

Concerning public transport, observing Figure 33 and Figure 35, one can note that most of the points are concentrated in the second and third quadrant in both cases, where car sharing travel time is less than the one of public transport. In the adopted Stated-preferences settings, waiting and walking time of the latter mode make in fact the overall travel time of car sharing shorter in virtually all circumstances. Positive switching densities are in any case smaller than those from private cars to car sharing. In the second quadrant (north-west), the majority of points have a negative value of switch (Figure 35): these respondents keep on using public transport when it is cheaper than car sharing, even if the latter has a shorter travel time. Complementing the above results related to substitution patterns between car and car sharing, it seems that car sharing services which are competitive with public transport on travel time grounds might induce an undesired diversion from public transport to car sharing itself, whereas the competition on travel costs is more detrimental to the use of cars. As a final note, there are a lot of observations with negative value of switch (Figure 35), even if car sharing is advantageous both for travel time and cost. Therefore, the analysis suggests that, like for car users, travel time and cost are not the only determinants of the switch from public transport and car sharing.

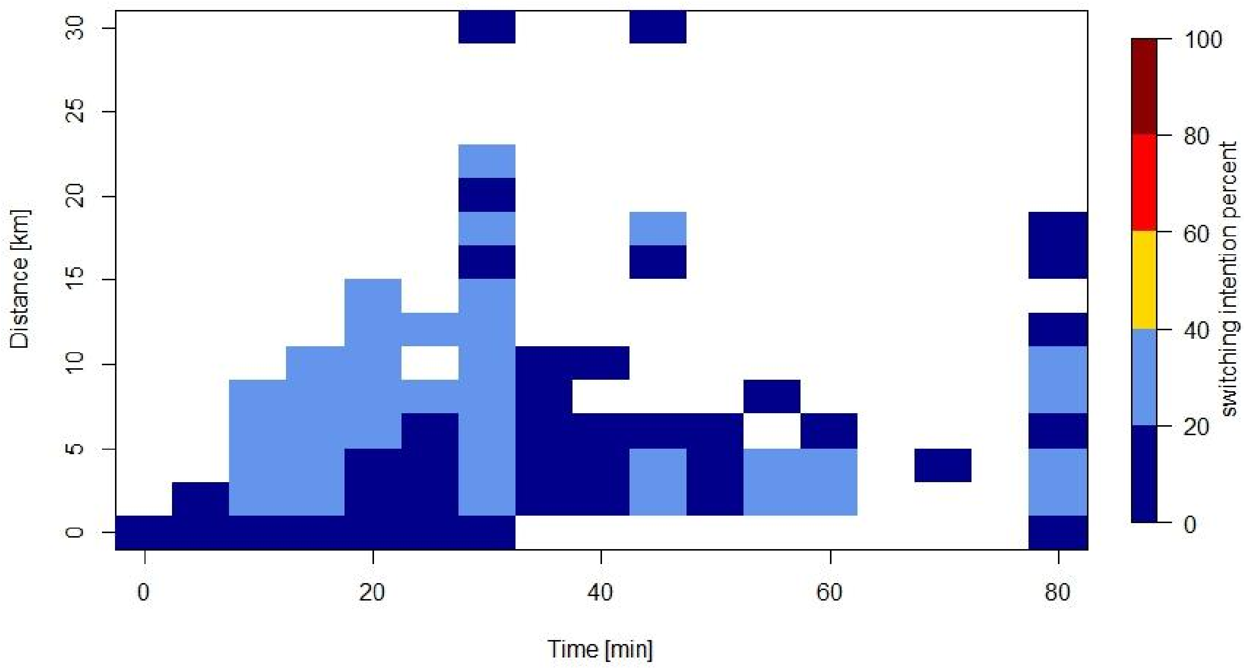

Figure 26. Switching intention percent towards car sharing for each class of RP attributes (distance and duration)

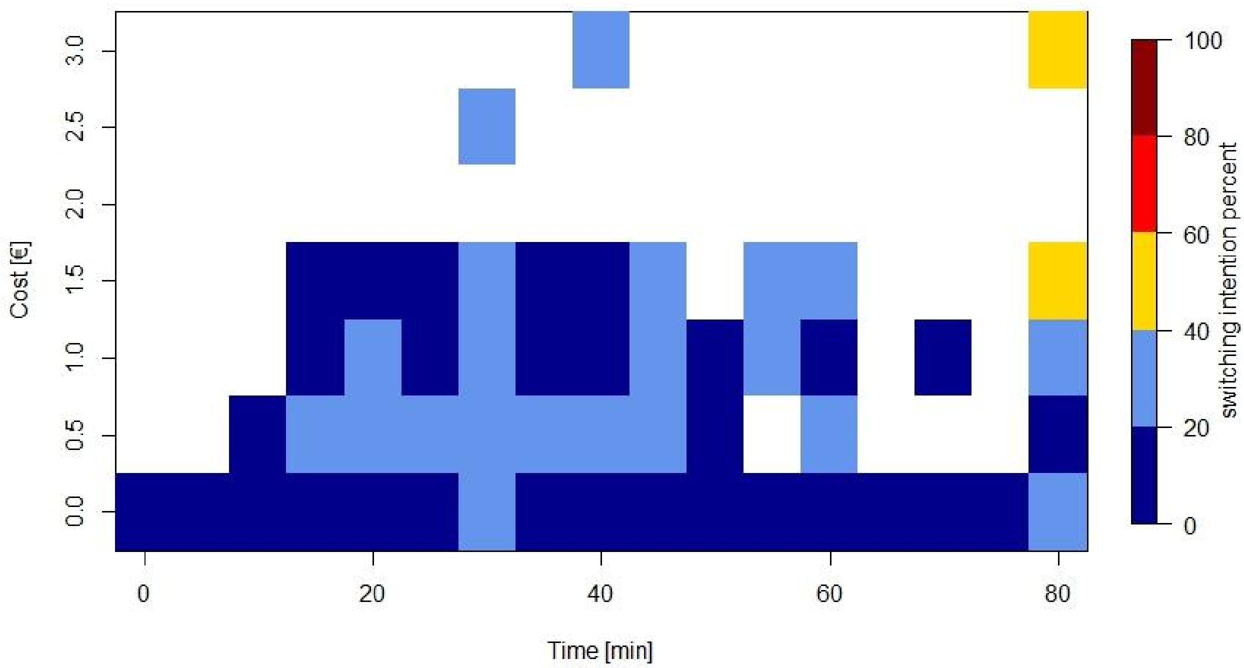

Figure 27. Switching intention percent towards car sharing for each class of RP attributes (cost and duration)

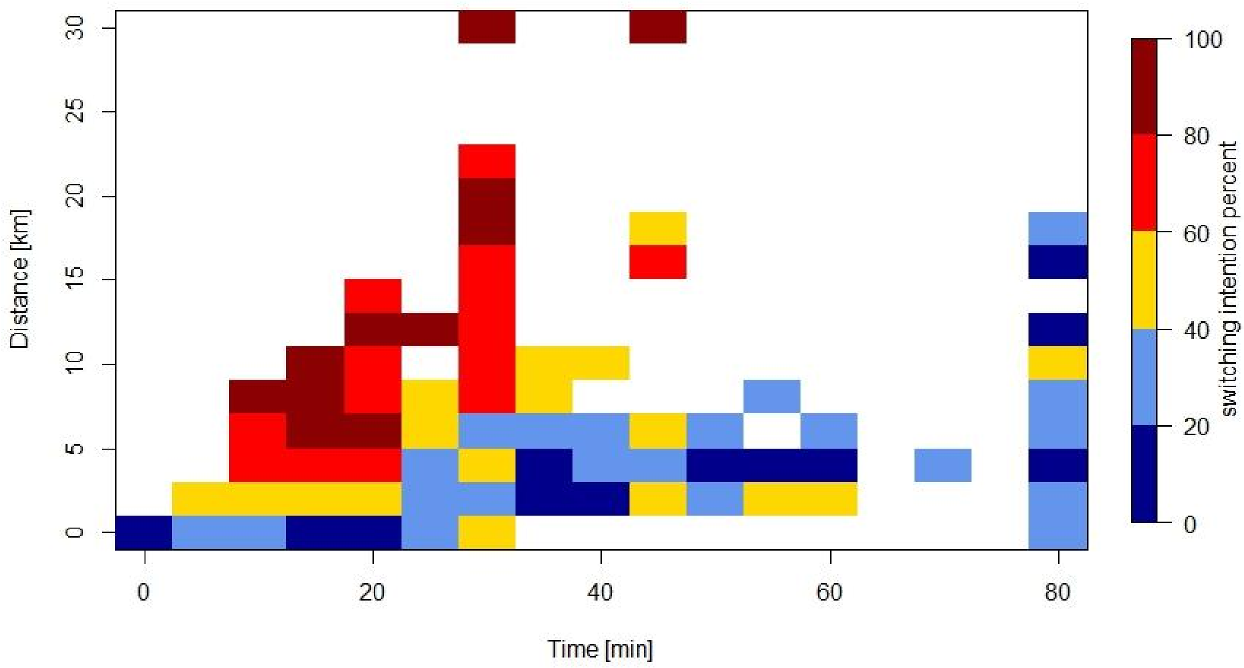

Figure 28. Switching intention percent towards car for each class of RP attributes (distance and duration)

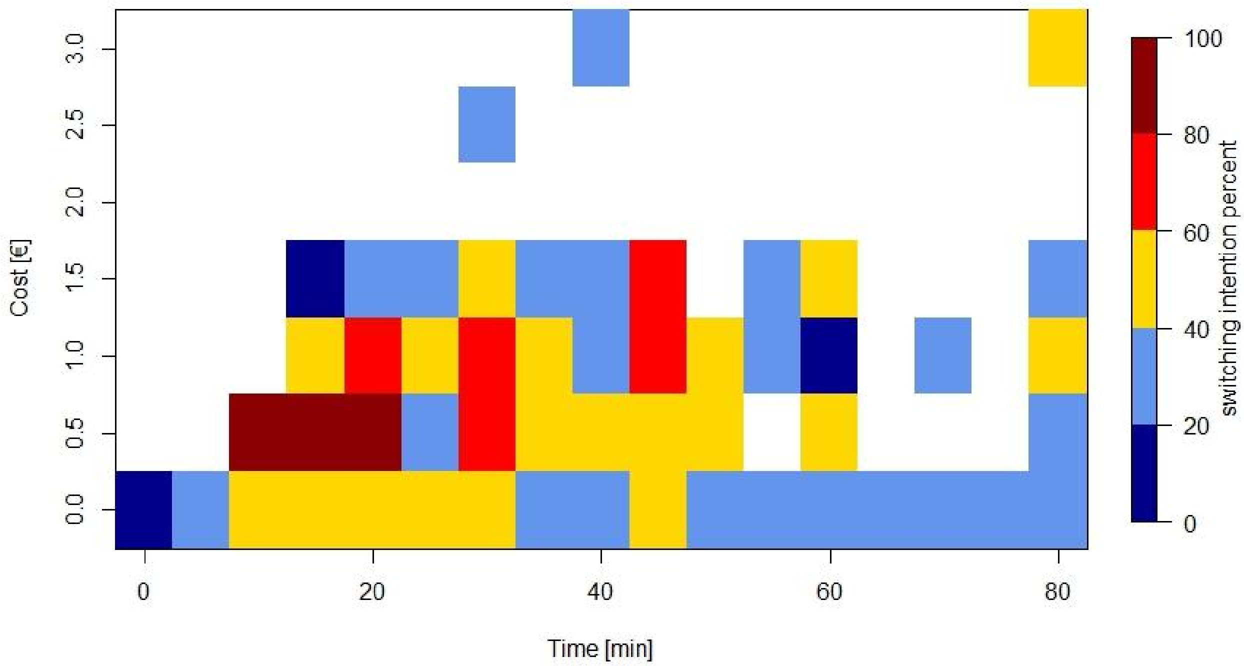

Figure 29. Switching intention percent towards car for each class of RP attributes (cost and duration)

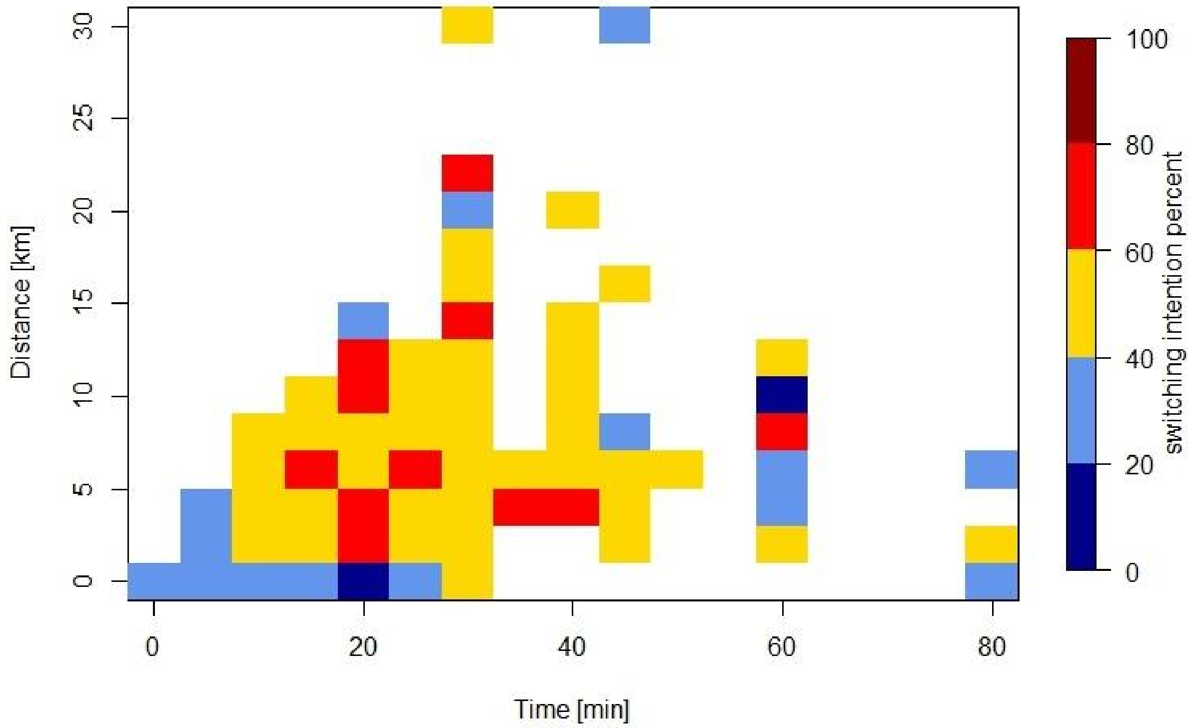

Figure 30. Switching intention percent towards public transport for each class of RP attributes (distance and duration)

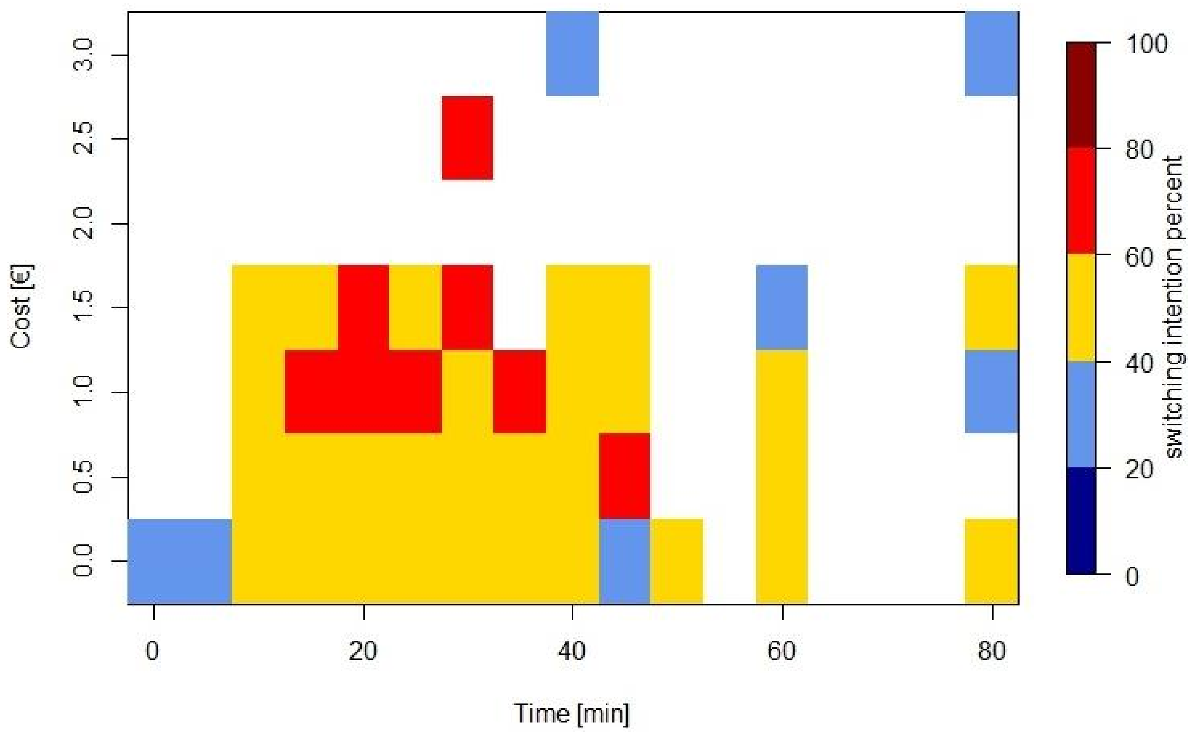

Figure 31. Switching intention percent towards public transport for each class of RP attributes (cost and duration)

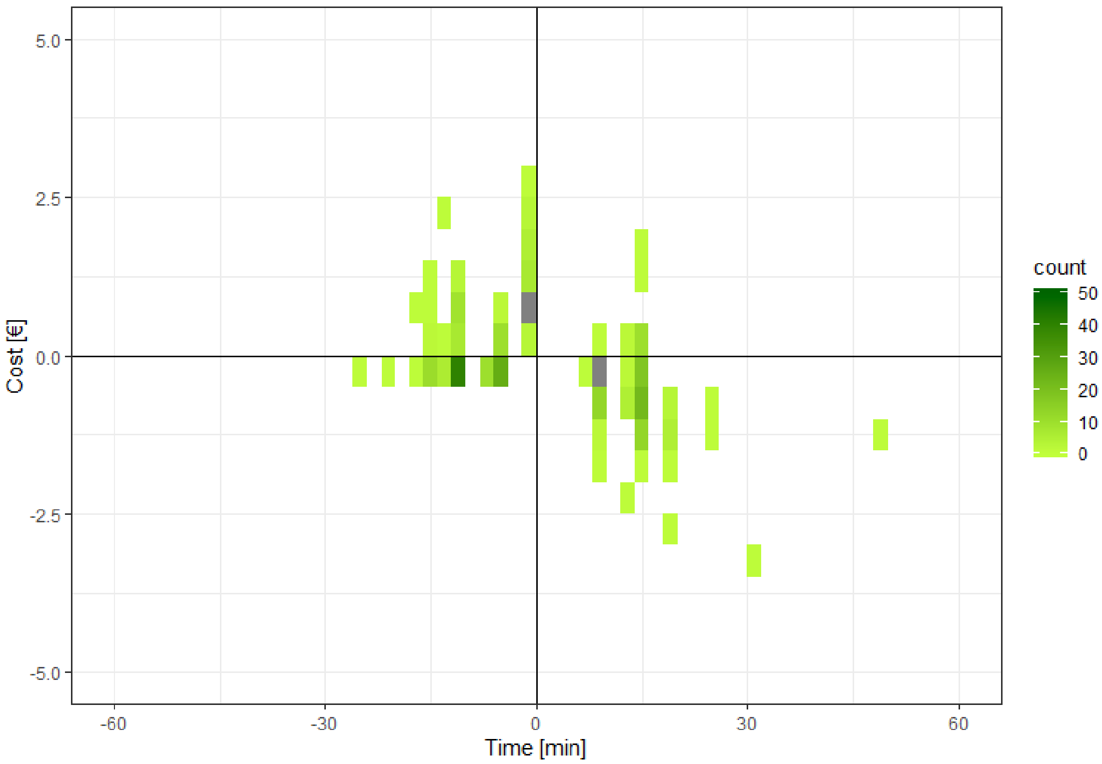

Figure 32. Densities of positive switching intentions from car to car sharing as a function of the difference between SP attributes (cost and duration) of car sharing and the corresponding RP attributes of car

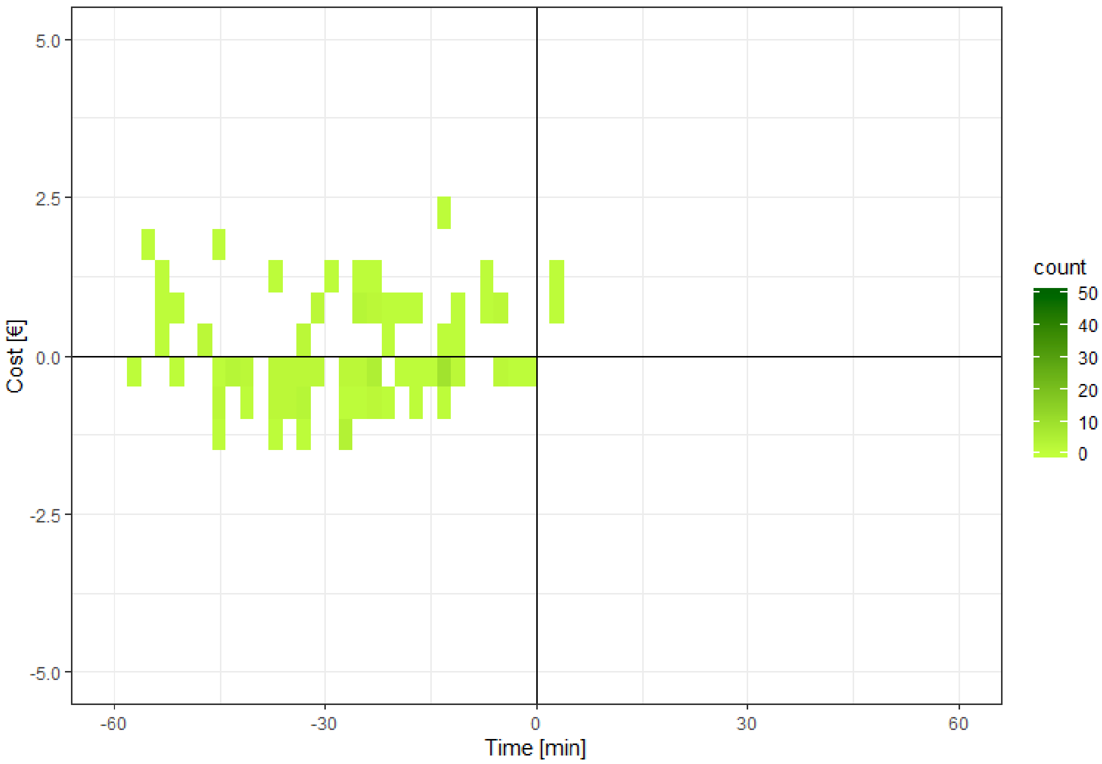

Figure 33. Densities of positive switching intentions from public transport to car sharing as a function of the difference between SP attributes (cost and duration) of car sharing and the corresponding RP attributes of public transport

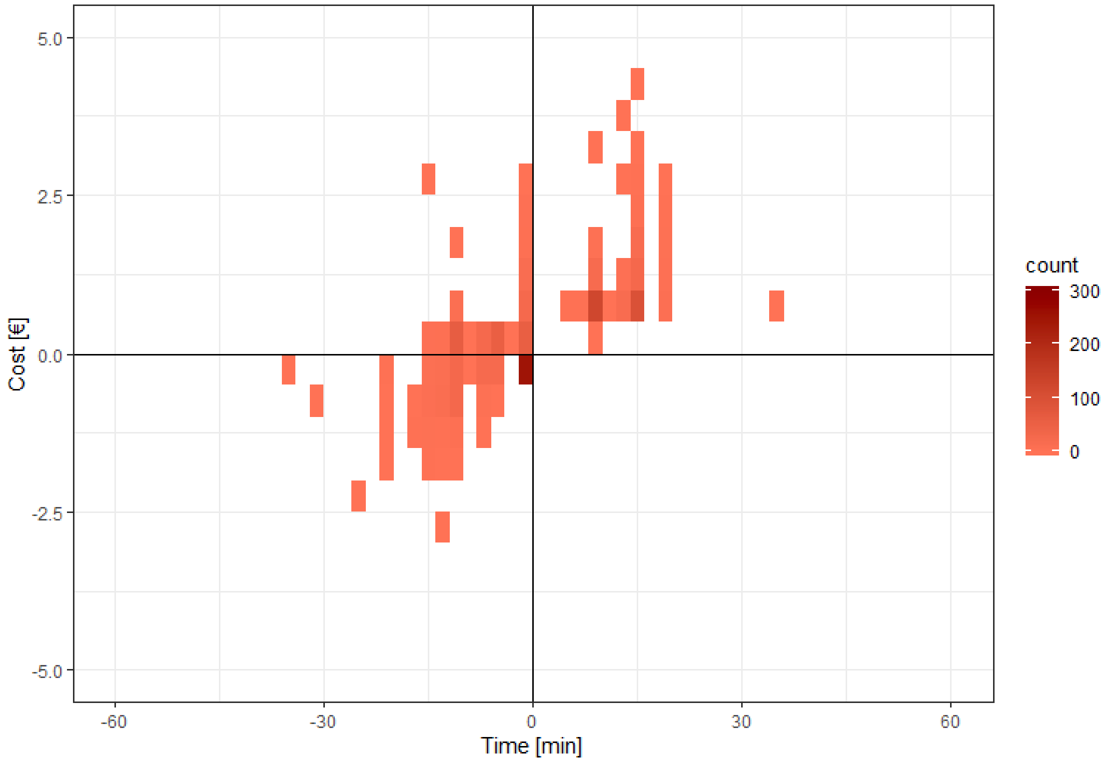

Figure 34. Densities of negative switching intentions from car to car sharing as a function of the difference between SP attributes (cost and duration) of car sharing and the corresponding RP attributes of car

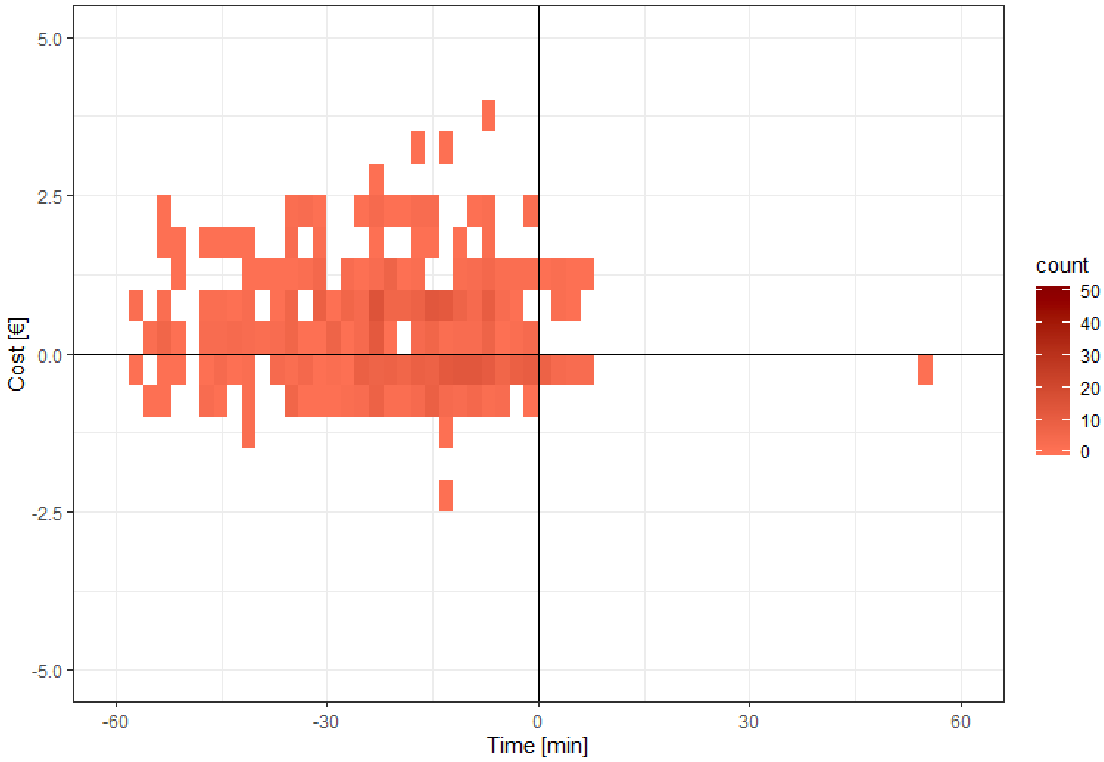

Figure 35. Densities of negative switching intentions from public transport to car sharing as a function of the difference between SP attributes (cost and duration) of car sharing and the corresponding RP attributes of public transport

5.3.5. Results comparison and conclusions

Models performances

Performance measures are calculated by applying each model both to the calibration and to the validation subset of macro-trips; in this way, it was possible to compare prediction performances and transferability of both logit models and Decision Trees.

In particular, the following indexes were adopted: Accuracy, Error rate, Recall, Precision, F-measure, Sensitivity and Specificity. Considering the prediction of the switching decision as a binary classification task, all these measures can be derived from a confusion matrix (Table 51), i.e. a matrix containing counts of observations belonging to predicted (in columns) and actual classes (in rows) (Cios et al., 2007; Han et al., 2012).

Table 51. Generic structure of a confusion matrix

		Predicted	
		Car sharing	**Base**
Actual	**Car sharing**	True Positive (TP)	False Negative (FN)
	Base	False Positive (FP)	True Negative (TN)

The accuracy represents the percentage of correctly classified objects and it is defined as (Cios et al., 2007; Han et al., 2012; Larose and Larose, 2015):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Conversely, the error rate is the percentage of misclassified observations (Cios et al., 2007; Han et al., 2012; Larose and Larose, 2015):

$$Error\ rate = \frac{FP + FN}{TP + TN + FP + FN} = 1 - Accuracy$$

However, these two measures are misleading, since a high accuracy (and a corresponding low error rate) is obtained if the model detects only elements belonging to one single class. Therefore, other measures should be adopted to consider predictive powers for each class separately (Han et al., 2012). Considering car sharing as the reference class, Precision is an index of exactness, i.e. it represents the percentage of predicted car sharing trips among actual car sharing trips; whereas, Recall is a measure of completeness, i.e. what percentage of actual car sharing trips are predicted as such (Han et al., 2012). Precision and Recall are defined as follows (Cios et al., 2007; Han et al., 2012):

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

Both Precision and Recall are combined into a single index, namely F-measure, which is calculated as the harmonic mean between these two measures. Therefore, for the car sharing class, F-measure is estimated as (Han et al., 2012):

$$F - measure = \frac{2 * Recall * Precision}{Recall + Precision}$$

Similarly, Sensitivity and Specificity are adopted to evaluate prediction performances for every single class. The former represents the true positive recognition rate, which is equal to class Recall, whereas the latter is a true negative rate. These two measures are calculated as follows (Cios et al., 2007; Han et al., 2012):

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{FP + TN}$$

All these measures were adopted to evaluate the performances of both logit models and Decision Trees, in terms of prediction powers of the potential trips that might be carried out on car sharing, rather than the currently reported travel mode. In particular, Table 52 and Table 53 report parameters for the five logit models, whereas Table 54 and Table 55 exhibit values for the two group of Decision Trees: the first group considers absolute values of trip attributes as exogenous variables, on the contrary, the second group adopts relative values. Table 52 and Table 54 contain results obtained from the validation datasets, on the other hand, Table 53 and Table 55 show results derived from the models applied to the calibration datasets. In all the four tables, Precision, Recall, F-measure, Sensitivity and Specificity are referred to car sharing alternative.

Observing the two tables of logit models and the two ones related to Decision Trees, one can note that, accuracies of Decision Trees are lower than those of logit models. However, respect to logit models, Decision Trees show higher values of Precision, Recall, F-measure, Sensitivity and Specificity of car sharing alternative. This indicates that this method has a greater prediction capability for car sharing, rather than for the base mode, therefore lower values of accuracies were obtained.

As regards mode-specific versions of the models, among the four logit models (Table 52 and Table 53), the one related to bike mode has the greatest predictive performances for car sharing trips, however the dataset to calibrate and validate this mode is the smallest one. On the other hand, public transport logit model shows the second highest value of F-measure, suggesting a good predictive capability. Overall, performance values calculated using the validation subsample (Table 52) are similar to those obtained from the calibration subsample (Table 53), suggesting that the models can be applied to other datasets without changing prediction performances; therefore results are stable and generalizable.

On the other hand, results reported in Table 54 and Table 55 are slightly different. In particular, considering the validation subset (Table 54) switching trips on car sharing are best predicted from private car, whereas model performances calculated using the calibration dataset (Table 55) indicate that car sharing potential trips are predicted more correctly for bike mode. Moreover, Decision Tree predicting shifting intentions of walking trips shows the maximum value of Recall (and Sensitivity), indicating that this model is able to recognize all the switching trip towards car sharing. Furthermore the comparison of the two tables suggest that all the performance measures have different values, therefore results of Decision Tree seems less transferable to different datasets, rather than logit models.

Table 52. Values of performance measures for logit models, calculated using the validation dataset (percentage values)

	All	Car	Public transport	Bike	Walking
Accuracy	77.45	74.35	74.89	87.10	92.90
Classification error	22.55	25.65	25.11	12.90	7.10
Precision	15.38	64.71	30.23	75.00	50.00
Recall	1.06	17.05	32.50	75.00	9.09
F-measure	1.98	26.99	31.33	75.00	15.38
Sensitivity	1.06	17.05	32.50	75.00	9.09
Specificity	98.40	96.42	83.96	91.30	99.31

Table 53. Values of performance measures for logit models, calculated using the calibration dataset (percentage values)

	All	Car	Public transport	Bike	Walking
Accuracy	77.99	74.68	79.55	81.48	93.97
Classification error	22.01	25.32	20.45	18.52	6.03
Precision	71.43	65.88	35.48	80.00	85.71
Recall	0.98	15.43	23.91	59.26	23.08
F-measure	1.94	25.00	28.57	68.09	36.36
Sensitivity	0.98	15.43	23.91	59.26	23.08
Specificity	99.89	96.99	91.03	92.59	99.69

Table 54. Values of performances measures for the two groups of Decision Trees, calculated using the validation dataset (percentage values)

	Absolute values of trip attributes					Relative values of trip attributes			
	All	Car	Public transport	Bike	Walking	Car	Public transport	Bike	Walking
Accuracy	65.26	64.01	67.40	61.29	81.29	70.26	66.08	64.52	81.29
Classification error	34.74	35.99	32.60	38.71	18.71	29.74	33.92	35.48	18.71
Precision	34.41	40.40	29.76	33.33	12.50	47.13	23.19	38.46	12.50
Recall	67.72	62.02	62.50	50.00	27.27	57.36	40.00	62.50	27.27
F-measure	45.63	48.93	40.32	40.00	17.14	51.75	29.36	47.62	17.14
Sensitivity	67.72	62.02	62.50	50.00	27.27	57.36	40.00	62.50	27.27
Specificity	64.59	64.78	68.45	65.22	85.42	75.22	71.66	65.22	85.42

Table 55. Values of performances measures for the two groups of Decision Trees, calculated using the calibration dataset (percentage values)

	Absolute values of trip attributes					Relative values of trip attributes			
	All	**Car**	**Public transport**	**Bike**	**Walking**	**Car**	**Public transport**	**Bike**	**Walking**
Accuracy	70.35	73.31	80.91	84.93	90.08	72.30	83.74	90.41	92.01
Classification error	29.65	26.69	19.09	15.07	9.92	27.70	16.26	9.59	7.99
Precision	40.46	51.40	47.78	65.52	41.94	50.23	52.07	78.26	42.27
Recall	80.45	78.81	92.47	95.00	100.00	71.19	94.62	90.00	100.00
F-measure	53.84	62.22	63.00	77.55	59.09	58.90	67.18	83.72	64.20
Sensitivity	80.45	78.81	92.47	95.00	100.00	71.19	94.62	90.00	100.00
Specificity	67.58	71.19	78.44	81.13	89.32	72.73	81.42	90.57	91.39

Results and conclusions

Each of the three approaches provided different considerations, from different perspectives, contributing to enrich the global view on the relationship between car sharing and traditional transport means. Since each adopted method has a different basis, some results are complementary and others are common. However, the aim of all the methods was to evaluate the variables affecting the intentions to switch from the reported mode (car, public transport, bike or walking) towards car sharing, in order to perform a specific macro-trip in the future. In this way, mode-specific factors to promote or avoid the shift can be identified. Exogenous variables are attributes of the macro-trip and characteristics of travellers (only for logit models and Decision Trees).

All the three approaches pointed out the general inertia of users to maintain their travel mode, rather than to switch to car sharing, suggesting that car sharing potential switches might be hindered by travel habits. This result was indicated by the higher number of registered non switch answers, rather than switch answers, in the Stated-preferences experiments (Section 4.5). Moreover, the current car sharing system, and, in particular, the related advantages, are not well-known among Turin inhabitants, probability due to its recent introduction in the city. However, current car sharing members are likely to adopt the service in future, pointing out that they are satisfied with the service. This might suggest that once a person becomes a member, she frequently replaces her travel mode with car sharing.

As regards socio-economic characteristic of potential car sharing members, results of both logit models and Decision Trees highlighted that car sharers tend to be young and living in households with high income, as obtained from statistical analysis of the sample of car sharing members (Section 4.4). Moreover, they have multimodal travel habits and use frequently active modes, as confirmed by the high percentages of use of these travel means of descriptive statistics in (Section 4.4). In addition, potential car sharing users seem to have a Value Of Time lower than car drivers and higher than public transport users (visual approach). On the other hand, some variables are mode-specific. For instance, car was found to play a negative role for public transport users, bikers and walkers. Furthermore, females are more willing to switch from public transport, whereas they tend not to switch from bike mode.

The analysis of trip attributes that can promote or avoid the shift is helpful to outline the relationship of car sharing with traditional travel means, defining the best ambit of use of each mode. All three models pointed out that reducing the cost of car sharing could induce the shift from private cars. Moreover, the same effect can be strengthened by increasing the cost of driving a private vehicle (logit model), reducing the duration of the trips by at least 3 minutes (Decision Tree) or decreasing the walking time to reach the shared car (Decision Tree). Car sharing can substitute private car for trips shorter than 14 kilometres (Decision Tree), even starting from outside the city and with a destination within the city (logit model). However, potential members are willing to walk up to 6 minutes to reach the shared vehicle (Decision Tree). Logit model suggested that car sharing might replace private car in non-working days, however Decision Tree predicted positive switches even in weekdays, for both systematic and non systematic trip purposes, since the outcome of this model is related to specific segment of users, i.e. with particular socio-economic characteristics; on the other hand, this segmentation could not be inferred from logit models.

As regards public transport, in general, low potential substitution rates were found for urban trips, i.e. with short distance and long duration (Decision Tree and visual approach), in particular for trips shorter than 10-18 kilometres. Furthermore, in order to avoid the shift towards car sharing, the cost of public transport trips should be lower (logit model, Decision Tree and visual approach). On the other hand, waiting time at the transit stop is a factor that affects switching intentions (logit model and Decision Tree), in particular, positive switches were predicted if the waiting time was greater than 3 minutes (Decision Tree), moreover potential car sharers are willing to pay up to 0.8 € to avoid 4 minutes of waiting time (Decision Tree). Furthermore, shifts might occur if the in-vehicle travel time on car sharing was lower than the one on public transport (Decision Tree and visual approach). Therefore, in order to prevent the switch from public transport towards car sharing, policies to maintain low fares and short waiting time (e.g. by increasing transit frequencies) should be carried out; in addition the travel speed of public transit means should be increased to compete with that of car sharing, in order to reduce potential switches. Car sharing might replace trips performed in non working days (logit model) and during weekdays, by employees and students (Decision Tree).

Car sharing was found not to be suitable for very short trips, in particular for travel distances shorter than 2 kilometres and with a duration lower than 30 minutes, since these type of trips are usually performed by bike or walking (visual approach). In particular, trips up to 300 meters long are carried out on foot, whereas the maximum distance by bike turned out to be 1.4 kilometres (Decision Tree). Both logit models and Decision Trees highlighted that reducing the cost of car sharing and the walking distance to reach a vehicle might induce the shift, not only from private car, but also from bike and walking. However, bikers are willing to walk up to 9 minutes and they might decide to switch if they could reduce this time of at least 5 minutes, if compared to the walking time to reach their bikes.

In conclusion, the three adopted approaches were useful to analyse the relationship between car sharing and traditional travel means and to study the effect of particular factors on the switching intentions. Each model provides different information, which could lead to similar or different conclusions. In particular, differences might be understood considering that logit models identify positive or negative relationships between dependent and independent variables, whereas Decision Trees estimate different effects for the same variables, according to the values of other variables. For instance, the effect of a trip attribute might depend on the characteristics of users. Therefore, the three methods gave light to the problem from different angles. To sum up, the visual approach provided preliminary descriptive analysis on the effect of trip attributes. Moreover, logit models were helpful to understand the effect of different exogenous variables and to derive further information to forecast the consequences of the introduction and diffusion of car sharing on future scenarios, e.g. by using trip switching probabilities. On the other hand, results from Decision Trees were used to identify the non-continuous effects of different variables, by estimating specific thresholds for each factor.

Chapter 6

Scenarios based on estimated switching models

6.1. Introduction

In this section, alternative mobility scenarios are generated using the previously estimated switching models (Section 5.3), in order to maximize the number of trips switching from private car towards car sharing and minimize those from public transport and active modes. The results of each scenario are used to analyse the modal split and the effect of car sharing in the use of public space. Indeed, as reported in the state of the art section (Chapter 2), one of the advantages of this transport mode is to reduce the on-street parking space that private cars usually occupy. However, in many previous works, the reduction of the demand for parking spaces is often associated with a reduction of car ownership due to car-sharing, so that several papers (Martin et al., 2010; Mishra et al., 2015) quantify how many private cars could be replaced by a shared vehicle. Yet positive benefits on public spaces might be observed, albeit to a lesser extent, even if the private car is not given up, since the parking pressure near the main mobility attractors might be reduced.

Therefore, without considering changes in car ownership levels, which are related to long term effects, in the present work, trip-level impacts on parking spaces, which might occur in short-medium periods, are estimated, by analysing variations in the spatial configuration of the demand for car parking spaces after the introduction of car sharing. Following this perspective, a “parking event” is defined as a parking space that is occupied by a vehicle whose trip was switched to car-sharing. Even if the number of parking events is not equivalent to the number of parking slots, this conceptual measurement unit can be useful to assess the potentially saved parking space. Moreover, this quantification can be used as an input to GIS-based analysis, in order to provide some guidance to local authorities in evaluating car-sharing impacts on public spaces. In particular policy makers can properly address financial resources, since concessions to car-sharing operators are often based on parking permissions (Ceccato and Diana, 2018); on the other hand, sound basis are provided to define reallocation strategies of saved spaces in urban planning.

6.2. Methodology to define the alternative scenarios

Following the proposed perspective, in order to estimate the impact of car-sharing on parking space, results of the switching models, combined with the reported parking habits and trip characteristics of respondents, were used to quantify how many parking events can be saved after the shift from private car towards car-sharing. In particular, in section C of the travel survey, respondents who reported private car as the main mode for the macro-trip were asked to indicate where the vehicle was parked, both at the origin and destination of the trip. Specifically, they can choose among seven alternative answers: free on-street parking, paying on-street parking, free public parking space, paying public parking space, residential garage or space, private garage or space, unknown.

In this way, it was possible to analyse how trips switching to car sharing might impact in terms of parking events, according to the types of parking area both at the origin and destination. Table 56 gives a preliminary evaluation of the effects of potential trips on car sharing, according to the type of parking zone, at the origin and destination of the macro-trip. In particular, the six possible answers (excluding "unknown") were aggregated in pairs, generating three meaningful groups (On-street, public parking space and private or residential garage). Observing Table 56 one can note that car sharing impacts are not always positive. Positive effects were assigned only to destinations where the vehicle is parked in an on-street or public parking space, since, in these cases, the shared car which substitutes the private car would remain parked for less time in these areas (Millard-Ball et al., 2005). On the other hand, neutral effects were associated with the garage option, since, if the switch occurs, the private car would remain in that garage, without occupying public space elsewhere. On the contrary, if car sharing replaces a trip previously carried out on a private car which was parked in an on-street area or in a public parking space at the origin, a negative impact might occur, since the substituted vehicle would go on occupying public space.

Table 56. Impacts of potential car sharing trips at the origin and destination of the macro-trip

Type of parking at the origin	Type of parking at the destination	Impact at the origin	Impact at the destination
On-street	On-street	Negative	Positive
On-street	Public parking space	Negative	Positive
On-street	Private or residential garage	Negative	Neutral
Public parking space	On-street	Negative	Positive
Public parking space	Public parking space	Negative	Positive
Public parking space	Private or residential garage	Negative	Neutral
Private or residential garage	On-street	Neutral	Positive
Private or residential garage	Public parking space	Neutral	Positive
Private or residential garage	Private or residential garage	Neutral	Neutral

In order to define the modal split and to quantify the number and type of parking events after the shift from private car to car sharing for alternative scenarios, the estimation results of switching logit models for private car trips were adopted (see Section 5.3.2 for details about the calibration results). This model was selected, although it showed lower predicted performances, rather than Decision Trees, since it provided switching probabilities and it allowed testing different scenarios, by varying the magnitude of some exogenous variables, among those defined in the model specification phase. In particular, the aim of the following analysis is to maximize the switching trips from private car towards car sharing, and to minimize those from other base modes (i.e. public transport and active modes), by testing the combination of different interventions that a public authority might carry out. Specifically, three scenarios were created and analysed with this aim:

1. Observed base scenario. This scenario corresponds to the results reported in the travel survey and, therefore, it is related to the observed situation;
2. Growth scenario, which was defined as the outgrowth of the current situation, in which no exogenous policy measures are carried out. This scenario was supposed to occur after a wide diffusion of car sharing among Turin inhabitants. In order to generate this scenario, by applying trip-level logit models, the cost of both car sharing and car trips was estimated. In particular, since each respondent was not asked to specify which type of car sharing service she would adopt, the average cost per minute of car sharing was considered. Specifically, it was calculated as the average of real fares of the three car sharing operators in Turin, as reported in Table 53. Moreover, the parking cost for private car was estimated by using geo-localized location of trip origins and destinations. In particular, these data were processed in a GIS software to identify the paid parking zone in which each location falls and the related parking fare. Figure 42 shows the parking zones obtained from the open data maps available on the geoportal of the city of Turin (Città di Torino, 2019), which were used for the current analysis. Then, the parking durations both at the origin and at the destination of the macro-trip were used to calculate the final value of the parking cost. Moreover, since paid parking areas are free in specific hours, the cost was applied only if the parking event was within the paid parking period and the respondent declared not to have parked in a private or residential garage. After that, the estimated costs of car sharing and private car was adopted as an input of the switching logit models;
3. Alternative scenarios. This group of scenarios was estimated considering an increase of the cost of car sharing and car parking. These two factors were combined to evaluate the number of switching trips since, if the parking fares grew, public authorities might increase the cost that car sharing operators have to pay in order to allow their members to park everywhere in the operative areas, free of charge. Therefore, car sharing operators might be likely to increase their fares, in order to maintain the same level of profits. In particular, these first scenarios were generated by increasing the cost of both car sharing and parking, from 0% (current situation) up to 100% by 5% at each step. This range was adopted considering realistic policy measures. Thus, a matrix of 21x21 combinations of car sharing fares and parking costs were created; Moreover, even if, according to the adopted logit models, other significant variables might affect the shift from public transport and active modes towards car sharing, only these two variables were selected, since they are more likely to be managed by public authorities. In particular, the cost and waiting time of public transport can be changed only by public transit operators and walking distance to reach a car sharing vehicles can be varied only by car sharing providers (e.g. by increasing the fleet size).

For each considered scenario, in order to estimate effects on the whole city, results of the application of logit models were expanded to the universe of the population living in Turin, by using weights, which were estimated from the stratified sampling procedure. By applying this approach, it was implicitly assumed that individuals belonging to the same stratum perform the same macro-trip and have the same parking habits. Then, following a common transport planning procedure (Ortuzar and Willumsen, 2011), the weight of each respondent was multiplied by the probabilities to switch to car sharing and to keep on using the base mode. In this way, the number of potential car sharing trips was estimated.

Table 57. Car sharing fares for each operator and average value

Operator	Options	Fare [€/min]
Car2Go	Smart for Two	0.19
	Smart for 4	0.21
	Smart cabrio	0.24
Enjoy	-	0.25
Bluetorino	Under 25	0.17
	Over 26	0.20
Average		0.21

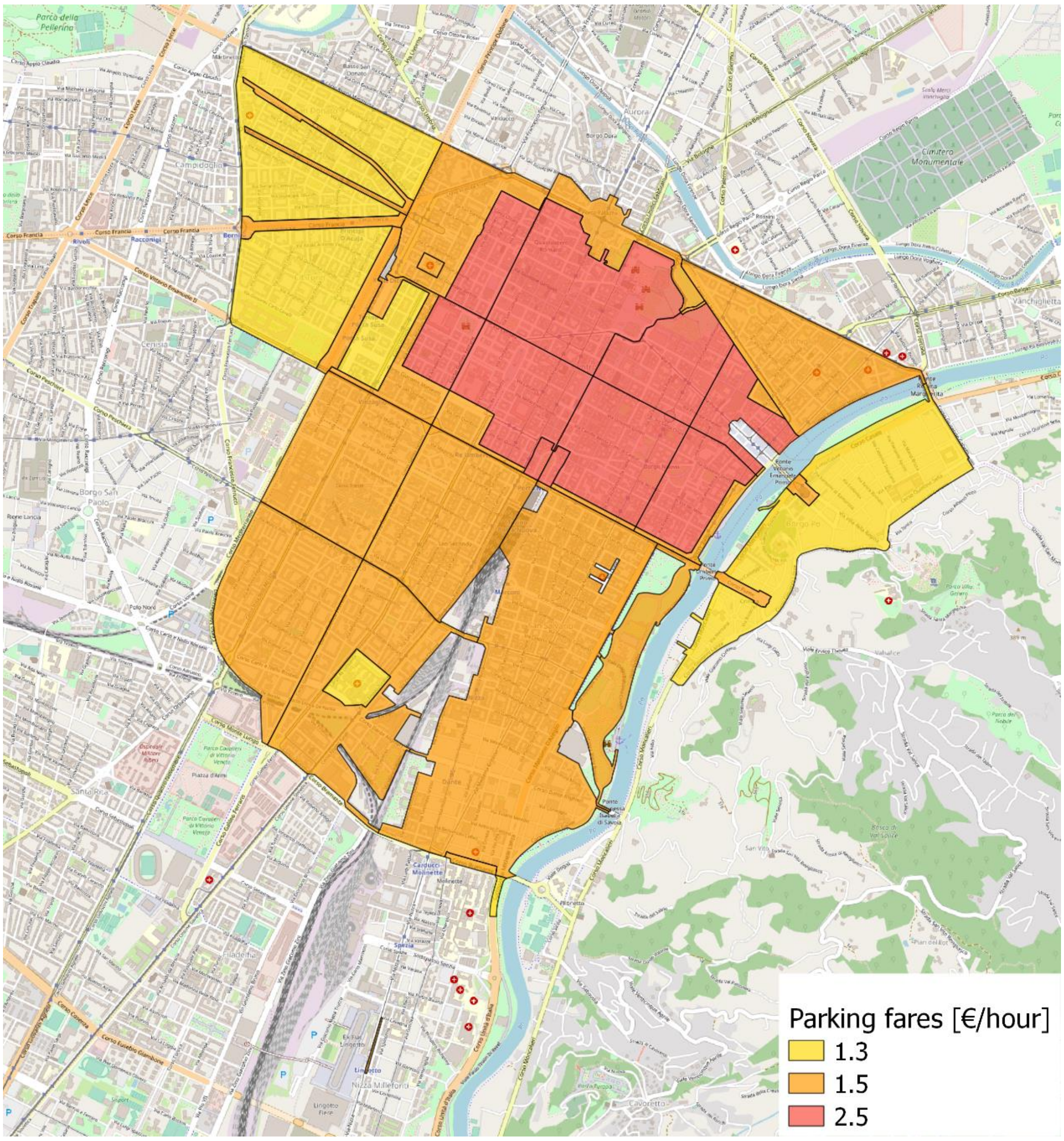

Figure 36. Paid parking areas and related fares for the current scenario

6.3. Observed base scenario

By applying the calculated weights, the modal split in the observed base scenario, was evaluated and it is reported in Table 58. Results in this table show that around half of the trips are performed by private car, about one quarter by public transport and the remaining ones by walking and bike. Furthermore, the characteristics of private car parking locations both at trip origins and destinations were evaluated and exhibited in Table 59. This table indicates that about 27% of the trips starts and ends in on-street parking places, whereas 23% starts in a private or residential garage and ends in roadside parks; considering trip origins (row totals), about half of the trips are originated from a garage, moreover, considering destinations (column totals) about half of the trips ends in on-street parking areas.

Table 58. Modal split for the current scenario

	Absolute value	Percentage value
Car	534’326	53.4
Public transport	265’552	26.5
Bike	33’122	3.3
Walking	168’008	16.8
	1’001’009	100.0

Table 59. Distribution of parking locations at origins (in rows) and destination (in columns) of car trips in the current scenario. Percentage values respect to the grand total in brackets

	On-street	Public parking space	Garage	Unknown	Total
On-street	142’332	5’995	54’662	857	203’846
	(26.6%)	(1.1%)	(10.2%)	(0.2%)	(38.2%)
Public parking space	3’434	11’376	33’128	1’250	49’187
	(0.6%)	(2.1%)	(6.2%)	(0.2%)	(9.2%)
Garage	120’260	43’912	110’528	622	275’322
	(22.5%)	(8.2%)	(20.7%)	(0.1%)	(51.5%)
Unknown	1’908	289	1’522	2’253	5’972
	(0.4%)	(0.1%)	(0.3%)	(0.4%)	(1.1%)
Total	267’934	61’571	199’839	4’982	534’326
	(50.1%)	(11.5%)	(37.4%)	(0.9%)	(100%)

6.4. Growth scenario

The estimated logit models for each of the four considered travel means were applied to the whole dataset of trip chains, generating the growth scenario. Results of the mode shift models are summarized in Table 60, which shows the trips that might be performed on car sharing and on the base mode. This table suggests that a total of 16% of trips might switch to car sharing, with similar percentage values among the four different base modes. This value is quite greater than the observed one for the sample (0.2%), since it was obtained from Revealed-preferences data of car sharing trips and considering the current service area. On the other hand, the value for the growth scenario was derived from Stated-preferences experiments, assuming several hypotheses from the econometric theory. Specifically, each individual decides to switch or not, in order to maximize her perceived utility, she has a perfect knowledge of the alternatives and their characteristics, and car sharing can substitute every macro-trip providing the same Level Of Service of the base mode, without considering the limitation of the operating area.

Recently, Chicco et al. (Chicco et al., 2020) obtained a value of about 10% of car sharing switching trips, in Turin, by calibrating mode shift models with data from the same travel survey adopted in the present work. However, the resulting value is different since the training set contained only observations related to respondents living within the car sharing service area. In addition, the estimated models were applied to a Revealed-preferences dataset of single trips collected in 2019. On the contrary, input data in the current analysis include persons living in the whole study area (the city of Turin and the surrounding municipalities), and calibrated switching models are applied to trip chains. Due to these aspects, models specification, calibration and application are different between the two works, thereby obtaining different results.

The resulting modal split is represented in Table 61. Private car shows the highest value (about 44%), followed by public transport (about 22%). Furthermore the percentage value of car sharing trips is slightly lower than the sum of bike and walking trips. Comparing these results with the corresponding modal split for the observed base scenario (Table 58), one can note that car sharing mainly substitutes car trips (the percentage was reduced by about 9%), whereas public transport and walking show similar decreasing rates (in particular, around 4% and 3%, respectively). On the other hand, bike reports low changes.

Table 62 reports the distribution of parking locations both at origins and destinations of the car macro-trips. In particular, percentages in

Table 62 indicate the variations respect to the corresponding values in the current scenario (Table 59). As expected, an overall reduction is predicted since the number of private car decreased; without considering the unknown answers, the greatest reduction value is reported for trip starting and ending in public parking space.

Table 60. Switching trips for the growth scenario (percentage values in brackets)

	Stay with the current mode	Switch to car sharing	Total
Private car	440’450 (82.4%)	93’876 (17.6%)	534’326 (100%)
Public transport	226’573 (85.3%)	38’979 (14.7%)	265’552 (100%)
Bike	29’089 (87.8%)	4’033 (12.2%)	33’122 (100%)
Walking	143’575 (85.5%)	24’433 (14.5%)	168’008 (100%)
Total	839’688 (83.9%)	161’321 (16.1%)	1’001’009 (100%)

Table 61. Modal split for the growth scenario

	Absolute value	Percentage value
Car	440’450	44.0
Public transport	226573	22.6
Bike	29’089	2.9
Walking	143’575	14.3
Car sharing	161’321	16.1
	1’001’009	100.0

Table 62. Distribution of parking locations at origins (in row) and destination (in column) of car trips in the growth scenario. Percentage variations respect to the base observed scenario are reported in brackets

	On-street	Public parking space	Garage	Unknown	Total
On-street	115’763	4’820	42’703	741	164’026
	(-18.7%)	(-19.6%)	(-21.9%)	(-13.5%)	(-19.5%)
Public parking space	2’812	8’740	25’711	944	38’206
	(-18.1%)	(-23.2%)	(-22.4%)	(-24.5%)	(-22.3%)
Garage	101’279	34’884	96’778	492	233’433
	(-15.8%)	(-20.6%)	(-12.4%)	(-20.9%)	(-15.2%)
Unknown	1’466	159	1’400	1’759	4’784
	(-23.2%)	(-44.9%)	(-8%)	(-21.9%)	(-19.9%)
Total	221’319	48’602	166’592	3’936	440’450
	(-17.4%)	(-21.1%)	(-16.6%)	(-21%)	(-17.6%)

Following the proposed methodology to categorize the impacts of car sharing on parking space summarized in Table 56, the characteristics of parking locations of switched trip chains were analysed for each Traffic Analysis Zone, in order to quantify the overall effect. Table 63 summarizes the related results; in particular, this table shows the parking location and the corresponding impact both at origin and at destination (in columns) for each zone (in rows). As regards the base observed scenario, it was not possible to evaluate the effect on parking space of performed car sharing trips, since a question about which travel modes would have been adopted instead of car sharing was not posed, in order to understand the travel mean that car sharing substituted. Therefore, the corresponding table for the base observed scenario was not generated.

Although positive and negative parking events cannot balance each other, since they represent different practical consequences on parking space, the net impact of car sharing was preliminarily estimated as the difference between parking events with a positive effect and those with a negative effect (in the last column of the table). Moreover, since one of the goals is to study the impact on public space, neutral effects of garage locations were not considered. Thus, the overall net impact of car sharing on public space was estimated in 8’784 avoided parking events (see the last row).

The distribution of parking locations reported in Table 56 was mapped using a GIS software, in order to understand the spatial characteristics of evaluated net impacts. Figure 37 and Figure 38 depict the values of estimated impacts of car sharing switched trips in the city centre and in the municipalities surrounding the city, respectively. In particular, only positive and negative effects were represented, distinguishing impacts at origin and destination. The distribution and size of estimated effects depends on several factors: land use variables, such as the distribution of attractors and residential areas, and infrastructural factors, such as the number of roadside parking slots, dedicated parking and garages. In particular, the number of productors (residences) produces a negative effect, whereas the presence of attractors generates a positive impact. Nevertheless, the two figures are helpful to understand specific zones where car sharing might produce negative effects. In such cases, policy makers should carry out interventions to lessen this impact, e.g. by reducing the number of parking slots for car and adding reserved parking for shared vehicles.

By observing the two figures one can note that in all the zones, the number of on-street parking events is greater than the value of parking events in a dedicated public area, both at origin and destination. Moreover, negative impacts are reported for some central zones, where the number of originated trips overcomes the number of attracted trips. The zone Q001 shows the highest number of parking events, since it is the most central zone, with many generators and attractors; however, the final net balance is the most negative, indicating that car sharing might result in many private cars occupying public space. On the contrary, the highest value of net positive impact is reported for zone Q003; due to this result, in this zone, parking space might be reduced. As regards the zones surrounding the city of Turin, a general overview suggests that, if car sharing operative area were extended, the number of parking events would be reduced with more availability of public space.

Table 63. Car sharing impact on parking space for each Traffic Analysis Zone in the growth scenario

	Origin				**Destination**				
	On-street	**Public parking**	**Garage**	**Unknown**	**On-street**	**Public parking**	**Garage**	**Unknown**	
Zone	**Negative**	**Negative**	**Neutral**	**-**	**Positive**	**Positive**	**Neutral**	**-**	**Net impact**
Ext	325	28	238	0	505	11	152	0	163
C001	1’093	379	1’503	36	1’159	253	1’827	0	-60
C002	1’003	839	1’965	96	1’460	1’121	1’596	0	740
C003	828	38	810	0	669	63	427	37	-133
C004	208	103	912	0	421	74	66	0	184
C005	577	41	2’176	22	1’167	110	1’517	72	659
C006	552	49	729	20	290	82	358	0	-230
C007	53	0	278	0	204	4	40	0	155
C008	1’124	269	1’661	0	1’462	376	1’272	0	444
C009	1	0	113	0	46	0	72	0	45
C010	982	66	1’898	41	1’031	309	1’461	0	292
C011	78	0	158	0	132	146	2	0	200
C012	183	0	691	26	385	132	599	0	334
C013	532	162	487	0	628	186	605	0	119
C014	313	0	641	0	598	126	371	0	411
C015	747	268	1’314	13	973	376	1’559	0	334
C016	393	0	528	0	219	67	578	0	-108
C017	154	61	392	28	327	75	205	0	187
C018	107	86	136	0	213	0	74	0	20
C019	585	15	399	0	379	0	492	0	-222
C020	551	73	674	0	965	272	386	0	612
C021	52	0	642	0	156	43	184	0	147
C022	66	0	129	0	29	33	80	0	-4
C023	83	132	136	0	228	73	146	0	86

C024	210	123	934	0	472	29	487	0	168
C025	252	0	242	0	493	33	176	0	273
C026	10	0	25	0	80	0	98	0	70
C027	188	33	367	0	248	1	201	0	28
C028	48	44	263	0	108	0	186	16	15
C029	142	76	227	26	54	0	178	0	-165
C030	10	30	80	0	31	21	90	0	12
C031	84	6	705	0	337	70	200	0	317
Q001	5’813	3’742	1’207	0	5’644	2’223	656	72	-1’689
Q002	2’173	547	794	0	1’417	490	1’166	230	-814
Q003	2’005	124	787	0	3’759	1’053	541	0	2’682
Q004	218	0	1’347	31	709	8	297	37	499
Q005	2’414	176	780	254	1’678	220	670	31	-692
Q006	1’611	714	1’320	519	2’443	1’512	812	0	1’630
Q007	931	172	745	0	586	327	751	311	-190
Q008	1’703	361	557	35	743	23	411	0	-1’298
Q009	1’316	832	581	0	714	272	1’001	53	-1’162
Q010	613	276	1’443	2	1’072	43	662	0	226
Q011	695	156	902	0	1’486	455	823	0	1’090
Q012	464	48	758	5	1’118	14	701	0	621
Q013	2’002	27	1’438	0	1’478	531	1’173	0	-20
Q014	1’475	72	1’134	0	1’337	191	871	0	-19
Q015	598	37	1’568	0	1’063	273	626	28	702
Q016	444	15	1’026	0	550	162	795	96	253
Q017	1’232	454	712	0	1’430	394	1’020	0	139
Q018	575	29	631	0	600	41	1’185	35	37
Q019	449	75	393	8	689	263	667	0	428
Q020	135	33	737	0	642	44	1507	0	519
Q021	256	115	124	0	126	40	83	0	-206
Q022	571	0	371	0	806	81	578	0	316
Q023	591	55	1’080	25	1’056	225	563	28	635
Total	39’819	10’981	41’889	1’187	46’615	12’969	33’247	1045	8’784

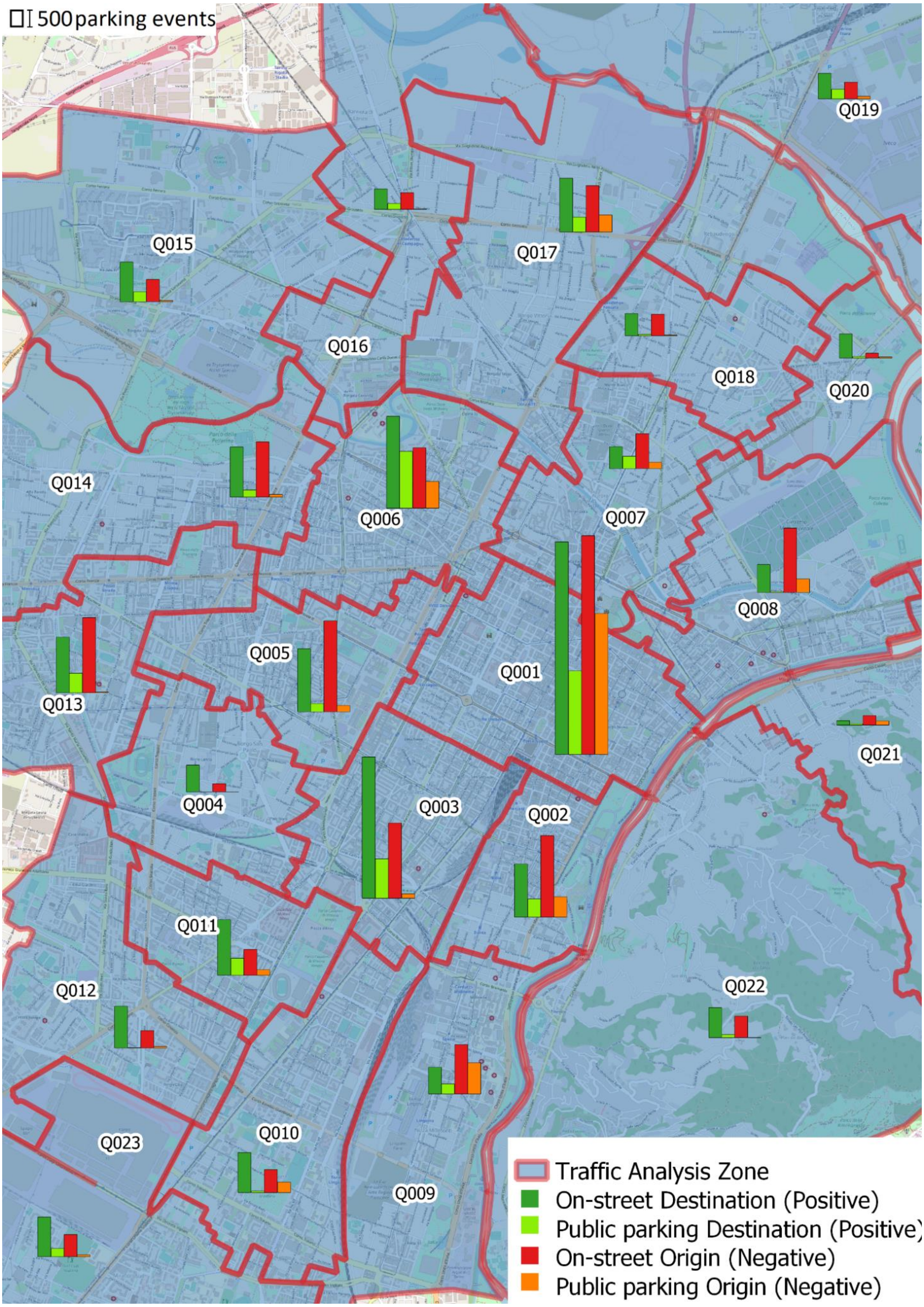

Figure 37. Impact of car sharing on parking events in the growth scenario (focus on the central area of Turin)

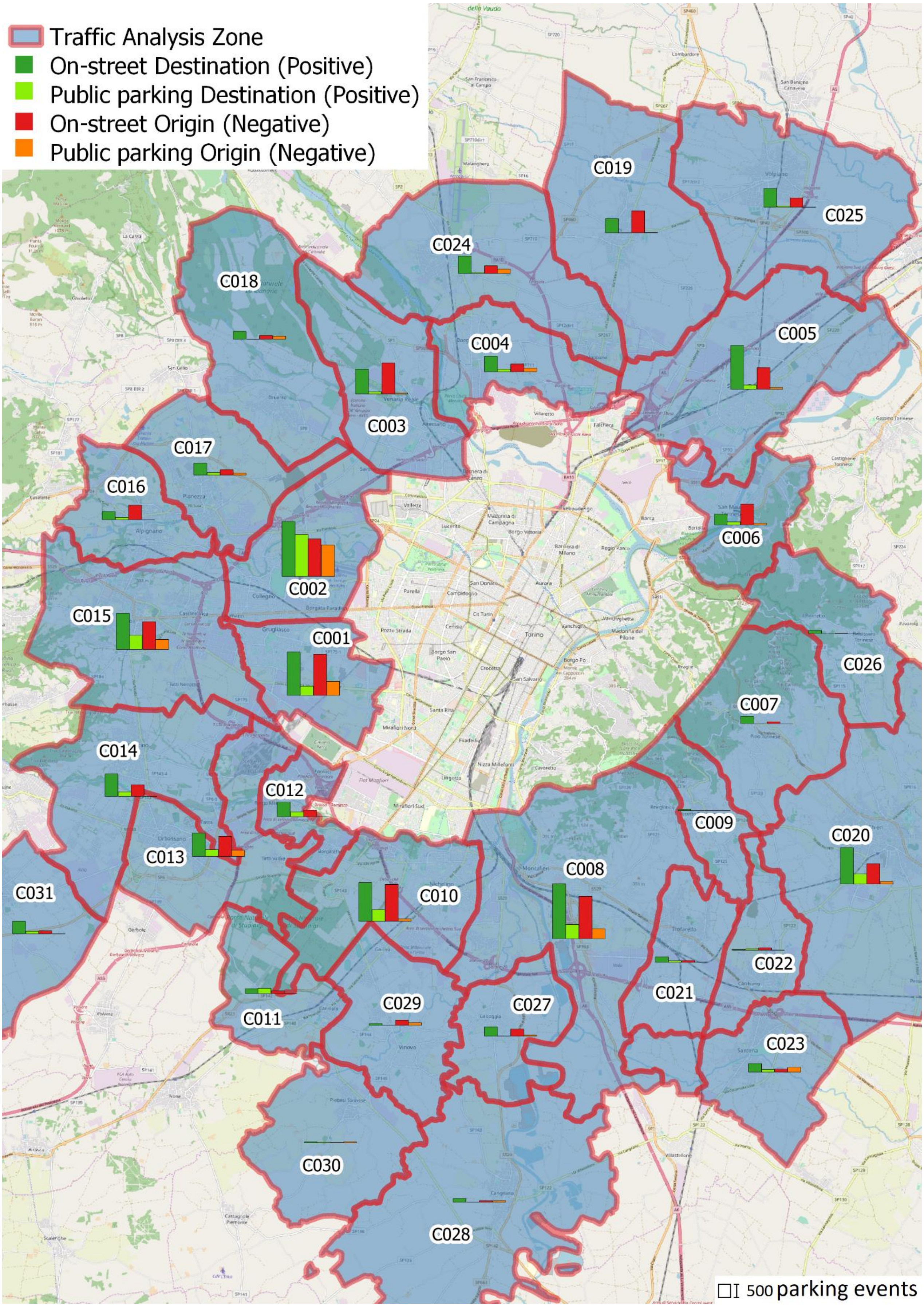

Figure 38. Impact of car sharing on parking events in the growth scenario (focus on municipalities surrounding the city of Turin)

6.5. Alternative scenarios: increase of car sharing fares and parking costs

6.5.1. Sensitivity analysis

As explained before, the aim of these group of scenarios is to maximize the switches from private car towards car sharing and to minimize those from other sustainable travel means. This corresponds to minimize the algebraic sum among the trips switched from car and those switched from public transport, bike and walking. In order to assess the scenario that reaches this aim, a sensitivity analysis was carried out by increasing both car sharing fares and parking costs for private vehicles. The increasing rate of these two factors ranges from 0% (like in the observed base scenario) and 100%, by 5% at each step; in this way, the combined effect of the two measures was analysed. In order to generate each scenario, the four estimated logit models, predicting the switching intention towards car sharing, were applied. Thus, the number of predicted trips on car sharing was estimated for each travel means and for each combination of the two exogenous variables under analysis.

Results of these analyses are respectively reported in Table 64, for private car trips, in Table 65, for public transport trips, in Table 66, for bike trips, in Table 67, for walking trips, whereas the net numbers of switching trips are shown in Table 68. Observing Table 64 one can note that, as expected from the corresponding estimated model, if car sharing cost increases, the number of switching trips decreases, on the contrary, if the parking fare grows, the number of switching trips increases. However the increasing rate due to parking costs is greater than the decreasing rate due to car sharing fares. This suggests that, in order to maximize the switching trips from private car, the effect of parking cost is higher than the one of car sharing fare. As regards public transport (Table 65), the cost of parking has no impact on the number of switching trips, whereas a rise of car sharing fares produces a decreasing number of switching trips, as expected. A similar result was obtained for bike trips (Table 66). On the other hand, the number of predicted trips shifting from walking to car sharing is constant throughout Table 67, since the cost of neither car sharing nor parking was an exogenous variable in the switching model for walking trips.

Final results are reported in Table 68, where each cell represents the algebraic differences between cells in Table 64 minus the sum of cells in Table 65, Table 66 and Table 67. Therefore, Table 68 is useful to evaluate the global impact of car sharing on the modal split for different combinations of parking and car sharing cost. In particular, most of the values in Table 68 are positive, indicating that the number of switching trips from private car overcomes those from the other travel means. Only some values are negative if the cost of car sharing is high and there are no or very small changes in parking fare. The overall trend is similar to the one of car switched trips (Table 64), where the maximum value is reported for the highest increasing rate of parking cost, since the absolute number of switching trips from car is greater than those from the other modes. This suggests that, in order to maximize the switches from private car and to minimize those from public transport and active modes, parking fare should be increased and the cost of car sharing should remain unchanged. Specifically, the maximum net difference, i.e. 46196 switching trips towards car sharing, is shown for no variations in car sharing costs and if the parking fares doubled.

Table 64. Switching trips from private car to car sharing for different changes of car sharing cost (in rows) and parking fares (in columns)

Percentage changes in car sharing cost \ Percentage changes in parking cost for private car	0	5	10	15	20	25	30	35	40	45	50	55	60	65	70	75	80	85	90	95	100
0	93'876	95'218	96'525	97'794	99'023	100'211	101'359	102'466	103'535	104'566	105'561	106'521	107'447	108'339	109'196	110'020	110'809	111'564	112'287	112'979	113'641
5	89'974	91'306	92'609	93'877	95'109	96'303	97'457	98'573	99'651	100'693	101'699	102'671	103'611	104'519	105'396	106'241	107'053	107'833	108'582	109'299	109'986
10	86'290	87'609	88'903	90'167	91'399	92'595	93'754	94'877	95'962	97'012	98'027	99'009	99'960	100'880	101'771	102'632	103'463	104'265	105'037	105'778	106'489
15	82'810	84'114	85'396	86'652	87'880	89'076	90'238	91'365	92'457	93'513	94'535	95'525	96'484	97'413	98'314	99'187	100'033	100'851	101'642	102'405	103'139
20	79'523	80'809	82'076	83'322	84'543	85'736	86'898	88'027	89'123	90'184	91'213	92'209	93'174	94'111	95'019	95'900	96'756	97'587	98'393	99'172	99'926
25	76'417	77'683	78'933	80'166	81'377	82'564	83'724	84'853	85'951	87'016	88'050	89'051	90'022	90'964	91'878	92'766	93'629	94'468	95'284	96'076	96'844
30	73'480	74'725	75'958	77'175	78'374	79'552	80'706	81'833	82'931	83'999	85'036	86'042	87'017	87'964	88'883	89'776	90'644	91'489	92'311	93'112	93'891
35	70'703	71'926	73'139	74'339	75'524	76'691	77'837	78'959	80'056	81'124	82'163	83'172	84'152	85'102	86'026	86'923	87'795	88'644	89'471	90'277	91'063
40	68'075	69'276	70'468	71'650	72'818	73'972	75'108	76'224	77'316	78'383	79'422	80'434	81'417	82'371	83'298	84'199	85'074	85'927	86'757	87'567	88'357
45	65'586	66'765	67'937	69'099	70'250	71'389	72'513	73'619	74'705	75'769	76'807	77'819	78'804	79'762	80'692	81'596	82'475	83'331	84'163	84'976	85'768
50	63'229	64'386	65'536	66'678	67'812	68'934	70'044	71'139	72'217	73'275	74'311	75'322	76'308	77'268	78'201	79'108	79'990	80'848	81'684	82'498	83'292
55	60'993	62'129	63'258	64'381	65'495	66'601	67'696	68'778	69'845	70'896	71'926	72'935	73'921	74'882	75'817	76'727	77'612	78'473	79'311	80'128	80'924
60	58'873	59'987	61'096	62'198	63'294	64'382	65'461	66'529	67'585	68'625	69'649	70'654	71'638	72'598	73'535	74'448	75'335	76'199	77'040	77'858	78'656
65	56'860	57'954	59'042	60'125	61'202	62'272	63'334	64'387	65'430	66'459	67'474	68'473	69'453	70'412	71'349	72'263	73'153	74'019	74'863	75'684	76'483
70	54'948	56'021	57'090	58'154	59'212	60'264	61'309	62'347	63'375	64'392	65'397	66'387	67'362	68'317	69'253	70'168	71'060	71'928	72'774	73'598	74'400
75	53'130	54'184	55'234	56'279	57'318	58'353	59'381	60'402	61'416	62'420	63'413	64'394	65'360	66'311	67'244	68'158	69'050	69'921	70'770	71'596	72'401
80	51'400	52'435	53'467	54'493	55'515	56'532	57'543	58'548	59'547	60'537	61'518	62'488	63'445	64'389	65'318	66'229	67'121	67'993	68'843	69'672	70'479
85	49'754	50'771	51'784	52'793	53'797	54'797	55'791	56'780	57'763	58'739	59'707	60'665	61'613	62'548	63'470	64'377	65'267	66'139	66'991	67'822	68'632
90	48'187	49'185	50'180	51'172	52'159	53'142	54'120	55'093	56'060	57'022	57'976	58'922	59'859	60'785	61'699	62'601	63'487	64'357	65'208	66'041	66'854
95	46'692	47'673	48'651	49'626	50'597	51'563	52'525	53'482	54'434	55'381	56'322	57'255	58'181	59'096	60'002	60'895	61'776	62'643	63'493	64'326	65'140
100	45'267	46'230	47'191	48'150	49'105	50'055	51'001	51'943	52'880	53'813	54'740	55'660	56'574	57'479	58'374	59'259	60'133	60'995	61'843	62'674	63'489

Table 65. Switching trips from public transport to car sharing for different changes of car sharing cost (in rows) and parking fares (in columns)

Percentage changes in parking cost for private car (columns); **Percentage changes in car sharing cost** (rows)

	0	**5**	**10**	**15**	**20**	**25**	**30**	**35**	**40**	**45**	**50**	**55**	**60**	**65**	**70**	**75**	**80**	**85**	**90**	**95**	**100**
0	38'979	38'979	38'979	38'979	38'979	38'979	38'979	38'979	38'979	38'979	38'979	38'979	38'979	38'979	38'979	38'979	38'979	38'979	38'979	38'979	38'979
5	37'509	37'509	37'509	37'509	37'509	37'509	37'509	37'509	37'509	37'509	37'509	37'509	37'509	37'509	37'509	37'509	37'509	37'509	37'509	37'509	37'509
10	36'120	36'120	36'120	36'120	36'120	36'120	36'120	36'120	36'120	36'120	36'120	36'120	36'120	36'120	36'120	36'120	36'120	36'120	36'120	36'120	36'120
15	34'805	34'805	34'805	34'805	34'805	34'805	34'805	34'805	34'805	34'805	34'805	34'805	34'805	34'805	34'805	34'805	34'805	34'805	34'805	34'805	34'805
20	33'560	33'560	33'560	33'560	33'560	33'560	33'560	33'560	33'560	33'560	33'560	33'560	33'560	33'560	33'560	33'560	33'560	33'560	33'560	33'560	33'560
25	32'381	32'381	32'381	32'381	32'381	32'381	32'381	32'381	32'381	32'381	32'381	32'381	32'381	32'381	32'381	32'381	32'381	32'381	32'381	32'381	32'381
30	31'264	31'264	31'264	31'264	31'264	31'264	31'264	31'264	31'264	31'264	31'264	31'264	31'264	31'264	31'264	31'264	31'264	31'264	31'264	31'264	31'264
35	30'204	30'204	30'204	30'204	30'204	30'204	30'204	30'204	30'204	30'204	30'204	30'204	30'204	30'204	30'204	30'204	30'204	30'204	30'204	30'204	30'204
40	29'199	29'199	29'199	29'199	29'199	29'199	29'199	29'199	29'199	29'199	29'199	29'199	29'199	29'199	29'199	29'199	29'199	29'199	29'199	29'199	29'199
45	28'246	28'246	28'246	28'246	28'246	28'246	28'246	28'246	28'246	28'246	28'246	28'246	28'246	28'246	28'246	28'246	28'246	28'246	28'246	28'246	28'246
50	27'340	27'340	27'340	27'340	27'340	27'340	27'340	27'340	27'340	27'340	27'340	27'340	27'340	27'340	27'340	27'340	27'340	27'340	27'340	27'340	27'340
55	26'480	26'480	26'480	26'480	26'480	26'480	26'480	26'480	26'480	26'480	26'480	26'480	26'480	26'480	26'480	26'480	26'480	26'480	26'480	26'480	26'480
60	25'662	25'662	25'662	25'662	25'662	25'662	25'662	25'662	25'662	25'662	25'662	25'662	25'662	25'662	25'662	25'662	25'662	25'662	25'662	25'662	25'662
65	24'885	24'885	24'885	24'885	24'885	24'885	24'885	24'885	24'885	24'885	24'885	24'885	24'885	24'885	24'885	24'885	24'885	24'885	24'885	24'885	24'885
70	24'145	24'145	24'145	24'145	24'145	24'145	24'145	24'145	24'145	24'145	24'145	24'145	24'145	24'145	24'145	24'145	24'145	24'145	24'145	24'145	24'145
75	23'442	23'442	23'442	23'442	23'442	23'442	23'442	23'442	23'442	23'442	23'442	23'442	23'442	23'442	23'442	23'442	23'442	23'442	23'442	23'442	23'442
80	22'771	22'771	22'771	22'771	22'771	22'771	22'771	22'771	22'771	22'771	22'771	22'771	22'771	22'771	22'771	22'771	22'771	22'771	22'771	22'771	22'771
85	22'132	22'132	22'132	22'132	22'132	22'132	22'132	22'132	22'132	22'132	22'132	22'132	22'132	22'132	22'132	22'132	22'132	22'132	22'132	22'132	22'132
90	21'523	21'523	21'523	21'523	21'523	21'523	21'523	21'523	21'523	21'523	21'523	21'523	21'523	21'523	21'523	21'523	21'523	21'523	21'523	21'523	21'523
95	20'941	20'941	20'941	20'941	20'941	20'941	20'941	20'941	20'941	20'941	20'941	20'941	20'941	20'941	20'941	20'941	20'941	20'941	20'941	20'941	20'941
100	20'386	20'386	20'386	20'386	20'386	20'386	20'386	20'386	20'386	20'386	20'386	20'386	20'386	20'386	20'386	20'386	20'386	20'386	20'386	20'386	20'386

Table 66. Switching trips from bike to car sharing for different changes of car sharing cost (in rows) and parking fares (in columns)

	Percentage changes in parking cost for private car																				
Percentage changes in car sharing cost	**0**	**5**	**10**	**15**	**20**	**25**	**30**	**35**	**40**	**45**	**50**	**55**	**60**	**65**	**70**	**75**	**80**	**85**	**90**	**95**	**100**
0	4'033	4'033	4'033	4'033	4'033	4'033	4'033	4'033	4'033	4'033	4'033	4'033	4'033	4'033	4'033	4'033	4'033	4'033	4'033	4'033	4'033
5	3'845	3'845	3'845	3'845	3'845	3'845	3'845	3'845	3'845	3'845	3'845	3'845	3'845	3'845	3'845	3'845	3'845	3'845	3'845	3'845	3'845
10	3'676	3'676	3'676	3'676	3'676	3'676	3'676	3'676	3'676	3'676	3'676	3'676	3'676	3'676	3'676	3'676	3'676	3'676	3'676	3'676	3'676
15	3'523	3'523	3'523	3'523	3'523	3'523	3'523	3'523	3'523	3'523	3'523	3'523	3'523	3'523	3'523	3'523	3'523	3'523	3'523	3'523	3'523
20	3'385	3'385	3'385	3'385	3'385	3'385	3'385	3'385	3'385	3'385	3'385	3'385	3'385	3'385	3'385	3'385	3'385	3'385	3'385	3'385	3'385
25	3'260	3'260	3'260	3'260	3'260	3'260	3'260	3'260	3'260	3'260	3'260	3'260	3'260	3'260	3'260	3'260	3'260	3'260	3'260	3'260	3'260
30	3'146	3'146	3'146	3'146	3'146	3'146	3'146	3'146	3'146	3'146	3'146	3'146	3'146	3'146	3'146	3'146	3'146	3'146	3'146	3'146	3'146
35	3'042	3'042	3'042	3'042	3'042	3'042	3'042	3'042	3'042	3'042	3'042	3'042	3'042	3'042	3'042	3'042	3'042	3'042	3'042	3'042	3'042
40	2'948	2'948	2'948	2'948	2'948	2'948	2'948	2'948	2'948	2'948	2'948	2'948	2'948	2'948	2'948	2'948	2'948	2'948	2'948	2'948	2'948
45	2'861	2'861	2'861	2'861	2'861	2'861	2'861	2'861	2'861	2'861	2'861	2'861	2'861	2'861	2'861	2'861	2'861	2'861	2'861	2'861	2'861
50	2'780	2'780	2'780	2'780	2'780	2'780	2'780	2'780	2'780	2'780	2'780	2'780	2'780	2'780	2'780	2'780	2'780	2'780	2'780	2'780	2'780
55	2'706	2'706	2'706	2'706	2'706	2'706	2'706	2'706	2'706	2'706	2'706	2'706	2'706	2'706	2'706	2'706	2'706	2'706	2'706	2'706	2'706
60	2'636	2'636	2'636	2'636	2'636	2'636	2'636	2'636	2'636	2'636	2'636	2'636	2'636	2'636	2'636	2'636	2'636	2'636	2'636	2'636	2'636
65	2'570	2'570	2'570	2'570	2'570	2'570	2'570	2'570	2'570	2'570	2'570	2'570	2'570	2'570	2'570	2'570	2'570	2'570	2'570	2'570	2'570
70	2'508	2'508	2'508	2'508	2'508	2'508	2'508	2'508	2'508	2'508	2'508	2'508	2'508	2'508	2'508	2'508	2'508	2'508	2'508	2'508	2'508
75	2'448	2'448	2'448	2'448	2'448	2'448	2'448	2'448	2'448	2'448	2'448	2'448	2'448	2'448	2'448	2'448	2'448	2'448	2'448	2'448	2'448
80	2'391	2'391	2'391	2'391	2'391	2'391	2'391	2'391	2'391	2'391	2'391	2'391	2'391	2'391	2'391	2'391	2'391	2'391	2'391	2'391	2'391
85	2'335	2'335	2'335	2'335	2'335	2'335	2'335	2'335	2'335	2'335	2'335	2'335	2'335	2'335	2'335	2'335	2'335	2'335	2'335	2'335	2'335
90	2'281	2'281	2'281	2'281	2'281	2'281	2'281	2'281	2'281	2'281	2'281	2'281	2'281	2'281	2'281	2'281	2'281	2'281	2'281	2'281	2'281
95	2'228	2'228	2'228	2'228	2'228	2'228	2'228	2'228	2'228	2'228	2'228	2'228	2'228	2'228	2'228	2'228	2'228	2'228	2'228	2'228	2'228
100	2'176	2'176	2'176	2'176	2'176	2'176	2'176	2'176	2'176	2'176	2'176	2'176	2'176	2'176	2'176	2'176	2'176	2'176	2'176	2'176	2'176

Table 67. Switching trips from walking to car sharing for different changes of car sharing cost (in rows) and parking fares (in columns)

Percentage changes in car sharing cost	Percentage changes in parking cost for private car																				
	0	**5**	**10**	**15**	**20**	**25**	**30**	**35**	**40**	**45**	**50**	**55**	**60**	**65**	**70**	**75**	**80**	**85**	**90**	**95**	**100**
0	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433
5	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433
10	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433
15	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433
20	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433
25	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433
30	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433
35	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433
40	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433
45	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433
50	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433
55	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433
60	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433
65	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433
70	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433
75	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433
80	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433
85	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433
90	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433
95	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433
100	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433	24'433

Table 68. Difference between the number of switching trips from private car and those from public transport, bike and walking

Percentage changes in car sharing cost \ Percentage changes in parking cost for private car	0	5	10	15	20	25	30	35	40	45	50	55	60	65	70	75	80	85	90	95	100
0	26'432	27'773	29'080	30'349	31'578	32'767	33'914	35'021	36'090	37'121	38'116	39'076	40'002	40'894	41'752	42'575	43'364	44'119	44'842	45'534	46'196
5	24'187	25'519	26'821	28'090	29'322	30'515	31'670	32'786	33'864	34'905	35'912	36'884	37'824	38'732	39'609	40'453	41'266	42'046	42'794	43'512	44'198
10	22'061	23'381	24'674	25'939	27'170	28'366	29'526	30'648	31'734	32'784	33'799	34'781	35'731	36'652	37'542	38'403	39'235	40'037	40'808	41'549	42'261
15	20'049	21'353	22'635	23'892	25'119	26'315	27'478	28'604	29'696	30'752	31'775	32'764	33'723	34'652	35'553	36'426	37'272	38'091	38'882	39'644	40'378
20	18'145	19'431	20'698	21'944	23'165	24'358	25'520	26'649	27'745	28'807	29'835	30'831	31'797	32'733	33'641	34'523	35'379	36'209	37'015	37'795	38'548
25	16'343	17'609	18'860	20'092	21'304	22'491	23'650	24'779	25'877	26'943	27'976	28'978	29'948	30'890	31'804	32'692	33'555	34'394	35'210	36'002	36'771
30	14'638	15'883	17'115	18'332	19'531	20'709	21'863	22'991	24'089	25'157	26'193	27'199	28'175	29'121	30'040	30'933	31'801	32'646	33'469	34'269	35'048
35	13'024	14'247	15'459	16'659	17'844	19'011	20'157	21'280	22'376	23'444	24'483	25'492	26'472	27'423	28'346	29'243	30'115	30'964	31'791	32'597	33'383
40	11'495	12'696	13'888	15'070	16'239	17'392	18'528	19'644	20'736	21'803	22'843	23'854	24'837	25'791	26'718	27'619	28'495	29'347	30'177	30'987	31'777
45	10'047	11'226	12'397	13'560	14'711	15'850	16'974	18'080	19'166	20'230	21'268	22'280	23'265	24'223	25'153	26'057	26'936	27'791	28'624	29'436	30'229
50	8'675	9'832	10'983	12'125	13'258	14'381	15'491	16'586	17'664	18'722	19'757	20'769	21'755	22'714	23'648	24'555	25'437	26'295	27'130	27'945	28'739
55	7'375	8'510	9'640	10'762	11'877	12'983	14'078	15'160	16'227	17'277	18'308	19'317	20'303	21'264	22'199	23'109	23'994	24'855	25'693	26'509	27'305
60	6'142	7'256	8'365	9'467	10'563	11'651	12'730	13'798	14'854	15'894	16'918	17'923	18'907	19'867	20'804	21'716	22'604	23'468	24'309	25'127	25'925
65	4'972	6'066	7'154	8'237	9'314	10'384	11'446	12'500	13'542	14'571	15'586	16'585	17'565	18'524	19'461	20'375	21'265	22'131	22'975	23'796	24'595
70	3'862	4'935	6'004	7'068	8'126	9'178	10'223	11'261	12'289	13'306	14'311	15'301	16'276	17'231	18'167	19'082	19'974	20'842	21'688	22'512	23'314
75	2'807	3'861	4'911	5'956	6'996	8'030	9'058	10'080	11'093	12'097	13'091	14'071	15'038	15'989	16'922	17'835	18'728	19'599	20'447	21'273	22'078
80	1'806	2'841	3'872	4'899	5'921	6'937	7'949	8'954	9'952	10'942	11'923	12'893	13'851	14'795	15'723	16'634	17'526	18'398	19'249	20'078	20'885
85	855	1'871	2'884	3'893	4'897	5'897	6'891	7'880	8'863	9'839	10'807	11'765	12'713	13'649	14'571	15'478	16'368	17'239	18'091	18'922	19'732
90	-50	949	1'944	2'936	3'923	4'906	5'884	6'857	7'824	8'786	9'740	10'686	11'623	12'549	13'463	14'364	15'251	16'120	16'972	17'805	18'617
95	-909	71	1'049	2'024	2'995	3'961	4'923	5'880	6'832	7'779	8'720	9'654	10'579	11'494	12'400	13'293	14'174	15'041	15'891	16'724	17'538
100	-1'728	-765	196	1'155	2'110	3'060	4'006	4'948	5'885	6'818	7'745	8'665	9'579	10'484	11'379	12'264	13'138	14'000	14'848	15'679	16'494

6.5.2. Analysis of the optimal scenario

The scenario with no changes in car sharing cost and an increase of 100% of parking fares was selected, since it maximizes the difference between the number of switching trips from private car and the other travel means. In particular, the obtained difference between car sharing trips and those on other travel means is 46’196. This scenario was selected, even if, as described before, an increasing of parking fare is often associated with a rise of the cost of car sharing. This analysis is related to short time impacts, when car sharing fare has not yet been adjusted to compensate for the growth of parking cost. However, a different scenario can be identified and analysed according to a known ratio between the two factors, which depends on the decision of each car sharing operator.

Results of the application of the modal switching models are reported in Table 69, which contains the number of trips switching and non switching to car sharing for the considered base modes. Overall, around 18% of trips are predicted to be performed on car sharing. The highest percentage of switching trips is shown for private car (about 21%). Moreover, public transport and walking share similar percentage values (around 15%), on the other hand, bike has the lowest value (about 12%). The obtained modal split is highlighted in Table 70. Observing this table one can note that private car has the highest part of the modal share (about 42%). Furthermore, the corresponding value for car sharing (18.1%) overcomes the sum of bike (2.9%) and walking trips (14.3%).

Table 71 shows the distribution of parking locations both at origins and destinations of the car macro-trips. In particular, percentages in Table 71 represent the variations respect to the corresponding values in the current scenario (Table 59). Since the overall number of predicted car trips decrease, negative percentage values are reported in each cell. As expected, an overall reduction is predicted since the number of private car decreased. Moreover, ignoring the unknown answers, the highest negative percentages are observed for trips starting from public parking spaces and ending in garages or public locations.

Table 69. Switching trips for the optimal selected scenario (percentage values in brackets)

	Stay with the current mode	**Switch to car sharing**	**Total**
Private car	420’685 (78.7%)	113’641 (21.3%)	534’326 (100%)
Public transport	226’573 (85.3%)	38’979 (14.7%)	265’552 (100%)
Bike	29’089 (87.8%)	4’033 (12.2%)	33’122 (100%)
Walking	143’575 (85.5%)	24’433 (14.5%)	168’008 (100%)
Total	819’923 (81.9%)	181’086 (18.1%)	1’001’009 (100%)

Table 70. Modal split for the optimal selected scenario

	Absolute value	**Percentage value**
Private car	420’685	42.0
Public transport	226’573	22.6
Bike	29’089	2.9
Walking	143’575	14.3
Car sharing	181’086	18.1
	1’001’009	100.0

Table 71. Distribution of parking locations at origins (in row) and destination (in column) of car trips in the optimal selected scenario. Percentage variations respect to the base observed scenario are reported in brackets

	On-street	Public parking space	Garage	Unknown	Total
On-street	109’435	4’798	40’210	693	155’135
	(-23.1%)	(-20%)	(-26.4%)	(-19.2%)	(-23.9%)
Public parking space	2’687	7’952	23’633	944	35’216
	(-21.7%)	(-30.1%)	(-28.7%)	(-24.5%)	(-28.4%)
Garage	96’760	31’903	96’778	492	225’933
	(-19.5%)	(-27.3%)	(-12.4%)	(-20.9%)	(-17.9%)
Unknown	1’308	33	1’400	1’661	4’401
	(-31.5%)	(-88.7%)	(-8%)	(-26.3%)	(-26.3%)
Total	210’190	44’685	162’021	3’789	420’685
	(-21.6%)	(-27.4%)	(-18.9%)	(-23.9%)	(-21.3%)

Like for the growth scenario, the impacts of car sharing on parking space was evaluated applying the methodology summarized in Table 56. In particular, the characteristics of parking locations of switched trip chains were analysed and reported in Table 72, for each Traffic Analysis Zone (in rows) both as origin and destination (in columns). The net impact of car sharing on parking space was estimated in 119’49 avoided parking events, without considering the neutral effects of garage. Values in Table 72 were mapped using a GIS software, in order to represent the spatial distribution of impacts for different zones. In particular, Figure 39 and Figure 40 show the values of estimated positive and negative impacts of car sharing switched trips in the city centre and in the municipalities surrounding the city, respectively. Observing these two figures and Table 72, one can note that zone Q003 and Q006 have the highest value of positive net impacts, suggesting that in these zones the parking areas might be reduced since less used. On the other hand, zone Q008 and Q009 report the greatest negative net impacts, probably due to the high number of residential locations.

Table 72. Car sharing impact on parking space for each Traffic Analysis Zone in the selected optimal scenario

	Origin				**Destination**				
	On-street	**Public parking**	**Garage**	**NN**	**On-street**	**Public parking**	**Garage**	**NN**	
Zone	**Negative**	**Negative**	**Neutral**	**-**	**Positive**	**Positive**	**Neutral**	**-**	**Net impact**
Ext	325	28	410	0	505	11	152	0	163
C001	1’125	379	1’594	36	1’168	253	1’995	0	-83
C002	1’166	839	2’209	96	1’461	1167	1’911	0	622
C003	992	38	1042	0	815	63	641	37	-152
C004	208	103	1304	0	421	74	159	0	184
C005	782	41	2’185	22	1’167	110	1’695	72	454
C006	654	49	893	64	419	82	459	0	-203
C007	53	0	468	0	364	4	40	0	315
C008	1’354	269	1’722	0	1’554	376	1’667	0	306
C009	1	0	131	0	46	0	128	0	45
C010	1’037	66	2’030	41	1’053	309	1’553	0	259
C011	78	0	289	0	132	162	2	0	216

C012	183	0	691	26	385	132	741	0	334
C013	671	162	545	0	647	186	980	0	0
C014	313	0	744	0	828	126	371	0	640
C015	788	268	1’390	13	1’237	376	1’610	0	557
C016	802	0	528	0	219	67	736	0	-516
C017	154	61	392	28	335	75	205	0	195
C018	107	133	136	0	213	0	74	0	-27
C019	585	15	802	0	449	0	503	0	-151
C020	929	73	957	0	1’016	272	697	0	287
C021	52	0	726	0	156	43	184	0	147
C022	66	0	129	0	29	33	80	0	-4
C023	83	224	136	0	228	73	146	0	-6
C024	210	123	1’002	0	585	29	722	0	282
C025	252	0	313	0	635	33	176	0	415
C026	10	0	25	0	80	0	114	0	70
C027	188	33	367	0	248	1	238	0	28
C028	48	44	263	0	225	0	186	16	132
C029	371	76	227	26	54	0	277	0	-394
C030	10	30	80	0	31	21	90	0	12
C031	84	6	986	0	340	70	200	0	320
Q001	7’290	5’698	1’382	0	8’650	3’900	699	120	-438
Q002	3’116	878	1’197	0	2’430	1’226	1’302	230	-338
Q003	2’983	205	956	0	5’024	1’507	688	0	3’343
Q004	235	0	1’430	31	985	8	336	37	758
Q005	3’064	293	918	256	2’278	267	697	31	-812
Q006	2’623	858	1’539	760	4’174	2’020	839	0	2’713
Q007	935	172	808	0	738	453	849	313	85
Q008	2’117	368	626	83	1’030	23	411	0	-1’433
Q009	1’482	1047	764	0	922	333	1’018	101	-1’274
Q010	635	276	1’639	2	1’072	43	662	0	204
Q011	743	156	907	0	1’518	455	998	0	1’074
Q012	464	48	758	5	1’177	14	701	0	680
Q013	2’080	27	1’773	0	1’478	531	1’238	0	-98
Q014	1’524	72	1’697	0	1’485	191	871	0	80
Q015	842	37	2’249	0	1’207	273	881	28	602
Q016	444	15	1’208	0	558	341	814	96	439
Q017	1’522	454	766	0	1’536	394	1’218	0	-44
Q018	575	29	803	0	728	41	1’238	83	165
Q019	449	75	393	8	734	263	707	0	474
Q020	135	33	917	0	642	44	1’577	0	518
Q021	455	115	124	0	175	105	107	0	-291
Q022	705	0	513	0	1’013	81	675	0	389
Q023	608	55	1’309	74	1’145	225	563	28	707
Total	48’711	13’971	49’389	1’570	57’745	16’886	37’818	1’193	11’949

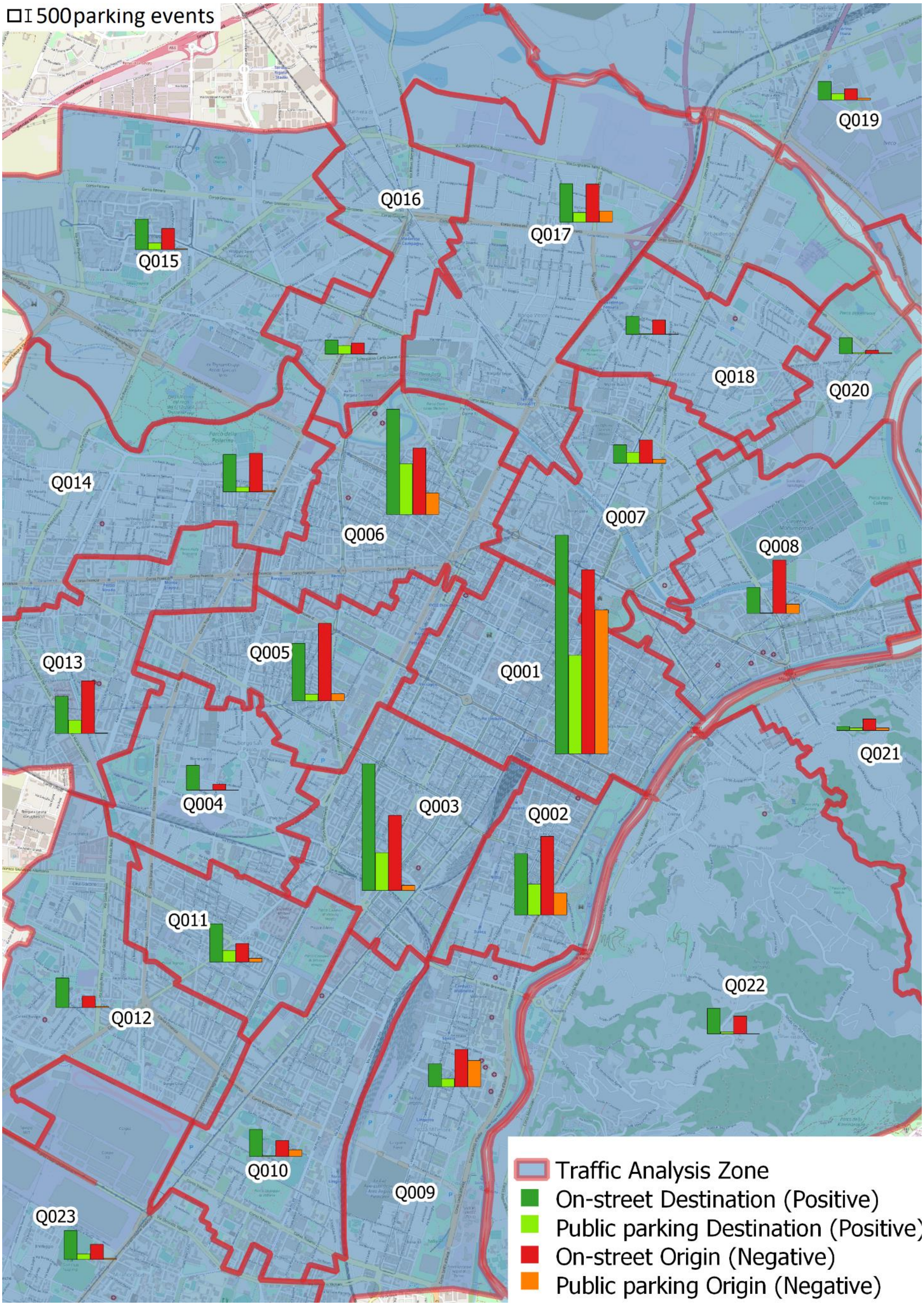

Figure 39. Impact of car sharing on parking events in the selected optimal scenario (focus on the central area of Turin)

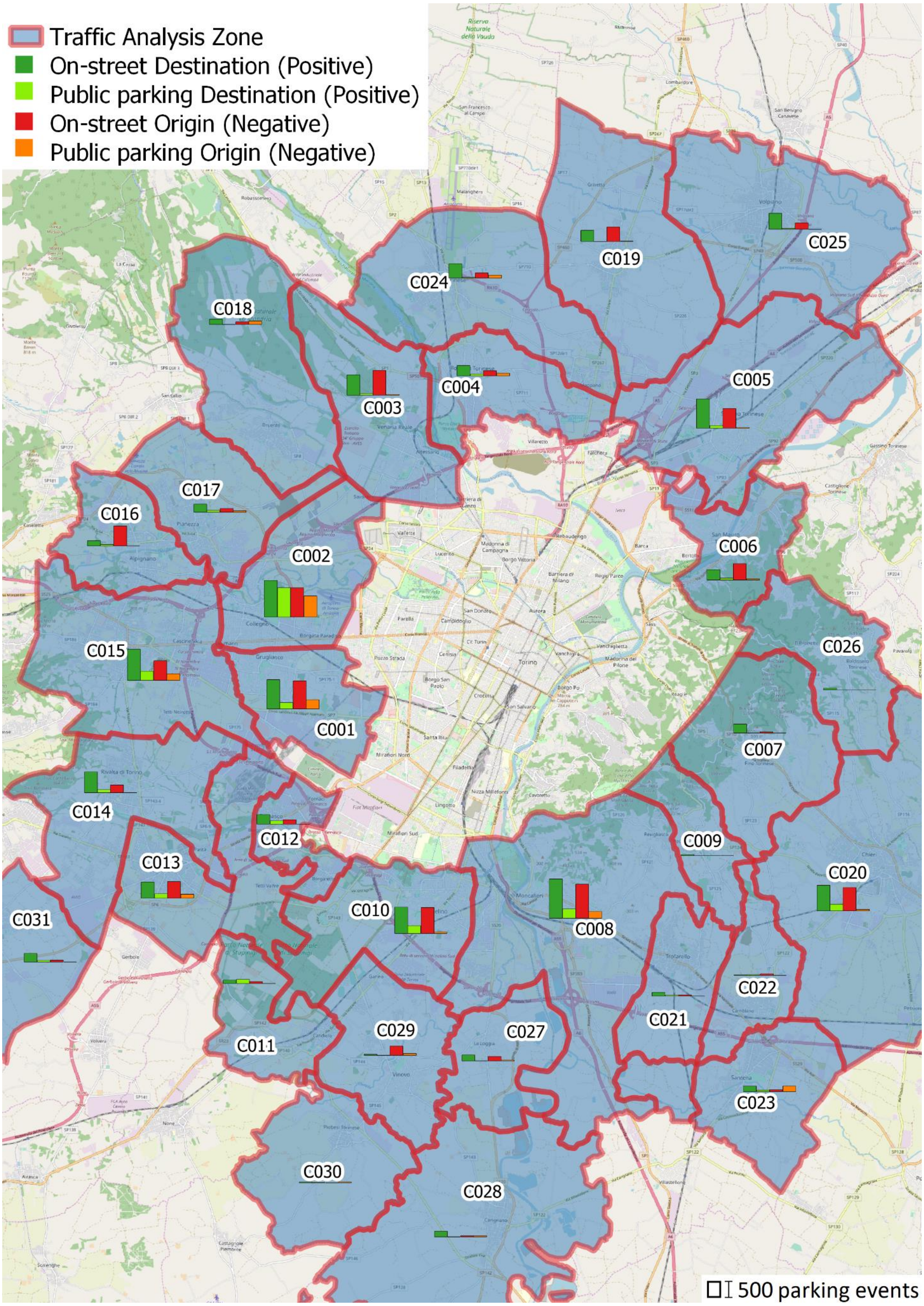

Figure 40. Impact of car sharing on parking events in the growth scenario (focus on municipalities surrounding the city of Turin)

6.6. Scenarios comparison

The results of the three scenarios described in the previous sections were analysed in terms of modal split and impacts on parking space. In particular, Figure 41 shows the number of trips which were predicted to be performed on private car, public transport, bike, walking and car sharing. As one can note, in the selected optimal scenario the number of car trips is the lowest, as expected. Specifically, the reduction of trips on private vehicle decreased by 21% respect to the base observed scenario, corresponding to 3% more than the growth scenario. On the other hand, the number of trips performed on public transport, bike and walking is the same for both the growth scenario and the selected optimal scenario, since the cost of car sharing, which affects the choice to switch to this service, was unchanged. In the selected optimal scenario, the number of car sharing trips increased by 12%; this difference is composed only by trips which were carried out on private car. Thus, the number of car sharing trips overcomes those of bike and walking trips.

The modal splits observed in the two alternative scenarios produced different effects on the parking space. Figure 42 represents the number of parking events in the city of Turin and in the municipalities surrounding it; these values were calculated as the differences between positive and negative impacts for each traffic zones. Specifically, Figure 42 shows that net positive impacts are predicted for both the observed base scenario and the selected optimal scenario. Moreover, the number of avoided parking events is higher for the latter scenario. However the size of impacts is different according to the considered area. In particular, the optimal scenario generated a greater impact for the zones within the city of Turin, rather than the growth scenario. This might be due to the increasing parking cost simulated in the optimal selected scenario, which has a more effective impact for the trips starting and ending in the city, where the paid parking area is active.

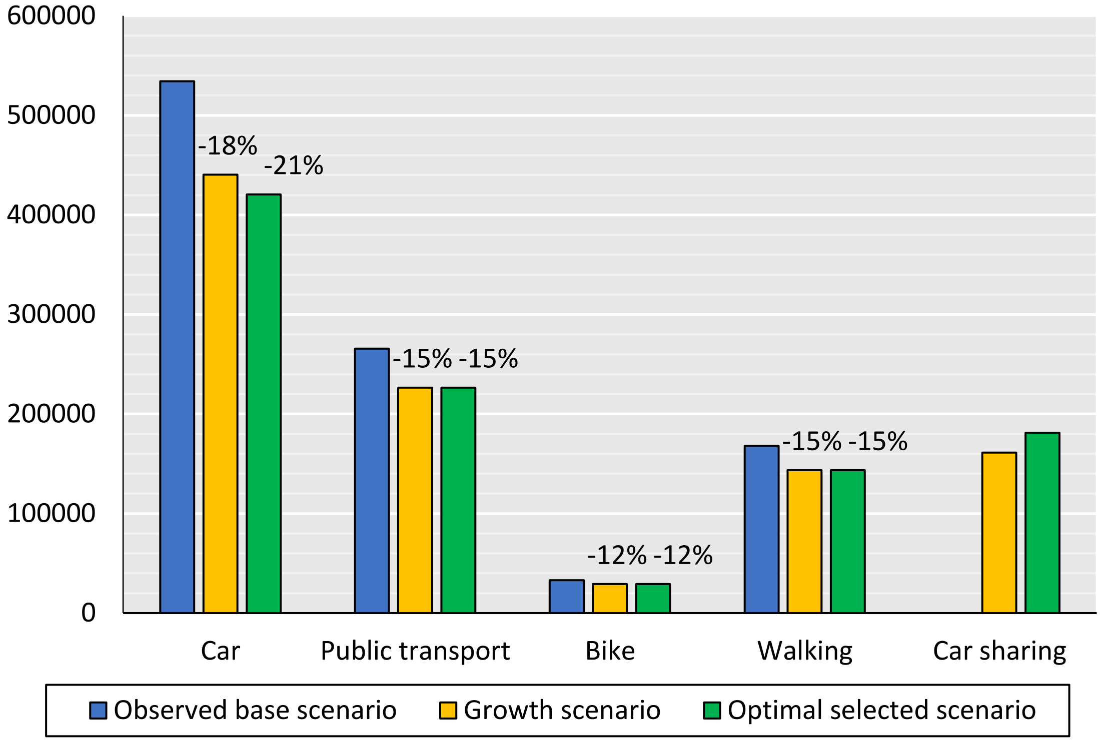

Figure 41. Number of trips performed on each of the four travel means for the observed base scenario, the growth scenario and the selected optimal scenario (percentage values are calculated respect to the observed base scenario)

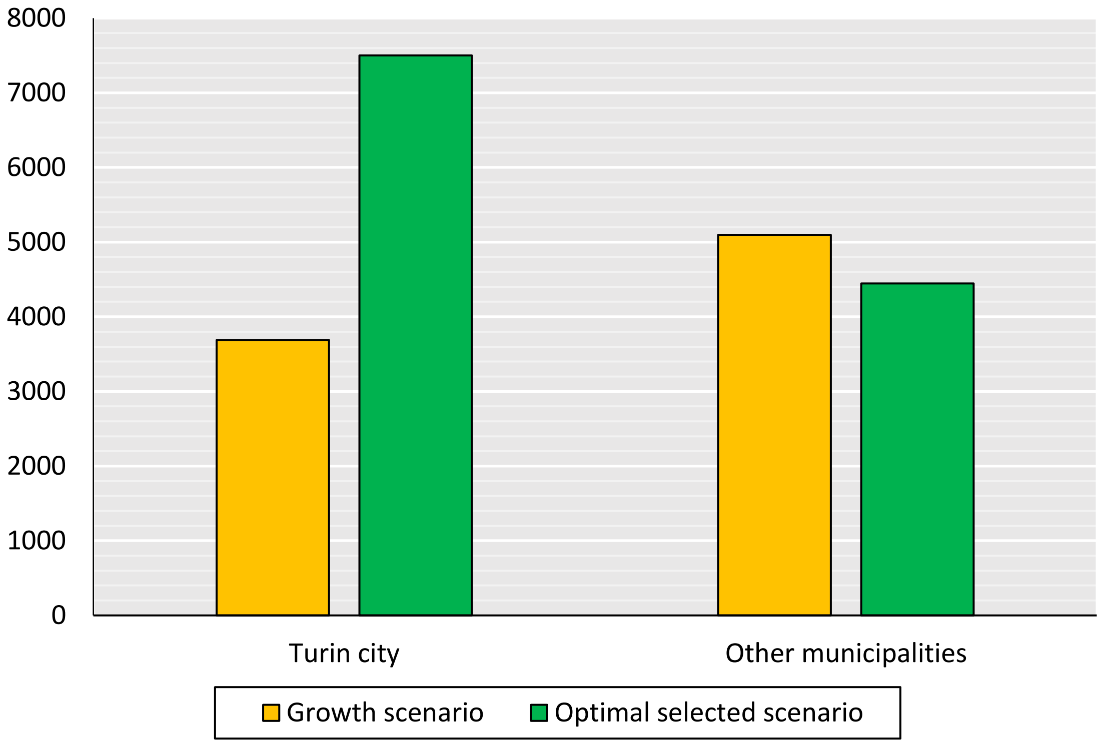

Figure 42. Net impact of car sharing on parking events for the city of Turin and the surrounding municipalities

6.7. Findings from the analysis of scenarios

In this chapter, results of the calibrated logit models, evaluating the switching intentions towards car sharing, were applied to quantify the effect of this service on modal split and parking space. In particular, each model was adopted to obtain the number of predicted trips on car sharing. Moreover, the impact of car sharing on public space was analysed through the definition of parking events, i.e. a parking space that is occupied by a vehicle whose trip was switched to car-sharing; following this perspective, the calibrated modal switching logit model was applied to estimate the number of avoided parking events. Moreover, since each respondent reported the type of parking location (on-street, public parking or garage), the specific parking time and geo-localized places, it was possible to assess the kind of effect of shifting trips, considering origins and destinations, separately.

Furthermore, different scenarios were analysed: the first one is the base observed scenario, which derived from the analysis of the sampled data obtained from the mobility survey. The second one is the growth scenario, in which no exogenous policy measures are carried out, and which was supposed to occur after a wide diffusion of car sharing among Turin inhabitants. The third group of scenarios was generated by varying the cost of car sharing trips and the parking fare, which are the two factors that public authorities can manage by carrying out specific interventions on the parking fares in the city, which might indirectly affect the cost of car sharing. For each combination of these two factors, modal switching models were applied to estimate the number of diverted trips to car sharing. After that, the scenario which maximizes the number of switching trips from private car and minimizes those from public transport, bike and walking was selected as the optimal scenario. Fort each of the two alternative scenarios the distribution of parking events was analysed and mapped for each Traffic Analysis Zone.

Results of the two alternative scenarios indicated that car sharing can effectively reduce the number of car trips. Sensitivity analysis suggested that, in order to maximize the difference between trips diverted from private car and those from the other base modes, the cost of car sharing should not change, but parking fares should be increased. The optimal selected scenario allows obtaining the highest value of diverted trips from private car. Moreover, the number of car sharing predicted trips was similar to the one to bike and walking. A positive net impact in terms of avoided parking events was observed in both the two alternative scenarios. However, the spatial distribution is quite different; in particular, the optimal scenario produced a greater number of positive parking events for the city of Turin, where the car adoption is affected by the parking cost.

The developed analysis can be helpful for policy makers to understand the effect of car sharing on modal split by testing different policies on car sharing fares and parking cost. Moreover, the proposed methodology can be adopted to identify the zones where car sharing produce positive or negative impacts in parking space, thus specific interventions can be carried out to manage these impacts by changing the parking availability.

Chapter 7

Conclusions

In the present work of thesis, factors affecting the choice to adopt car sharing were identified and the relationships of complementarity and/or substitution between car sharing and existing travel modes were analysed, in order to define the best ambit of use of each travel means. Unlike previous works, the effect of car sharing was modelled by separately considering the shift from private car, public transport, bike and walking. Therefore, through the proposed approach, the use of car sharing can be promoted or avoided, by varying mode-specific factors.

In the present work, data from a travel survey carried out in the Turin Metropolitan Area were used as input. The survey was administered to a representative sample of the population living in the study area, thereby outcomes of analysis could be generalized to the whole universe of individuals in the area under analysis. Socio-economic characteristic of respondents, their travel diary and related activity patterns spanning over the 24 hours before the interview were collected. Moreover, stated-preference experiments were administered to investigate mode switching attitudes for a randomly selected trip chain, which was effectively performed by the interviewed, thus allowing to obtain reliable results.

In order to reach the aim of the present work, statistical analysis, discrete choice models and data mining techniques were applied, and related results were compared. In particular, first statistical methods were adopted in order to preliminary analyse results of the travel survey, contributing to depict an overall overview of the current reported mobility scenario in the study area and, in particular, the characteristics of interviewed car sharing members. Specifically, results indicated that the majority of them is male, with an age that is significantly lower than the one of non members; moreover most of them have a high level of education and lives in households with many licenced drivers and a high income. Furthermore, they tend to have multimodal travel habits. However, they reported adopting car sharing only occasionally.

After that, two logistics regressions were implemented. The aim of the first one was to identify the users' characteristics that might affect the choice to join a car sharing program. Results of the model estimation confirmed those obtained from statistical analysis, suggesting that car sharing is used by young employed persons with a high educational level and who live in low-size households, with few private cars, many licenced drivers and a high income. In order to complement the results of the first model and, in particular, to understand how the characteristics of potential users of car sharing interact with both trip attributes and past and future multimodality behaviours, a second regression model was developed presenting a trip-level analysis. The model estimated the probability to adopt car sharing to perform the macro-trip under analysis in the future. Results highlighted that people currently using car sharing seem satisfied with the service and are likely to use it in the future. Moreover, the complementarity of this service with public transport was pointed out. Furthermore, car sharing seemed to be attractive for urban trips in congested streets. In addition, it was observed a substitution relationship with private car and metro, but not for train and school or company buses. In addition, it was confirmed that multimodality positively affects the propensity to use car sharing.

In order to predict potential trips carried out on car sharing and to analyse which factors might affect the decision to switch towards this mode, three kinds of approaches were developed. Results of the Stated-preferences part of the survey were adopted as an input of these methods. The first method was a traditional econometric model, namely a logit model; the second one was a data mining technique, specifically a Decision Tree model; the third one was a descriptive visual approach. The three proposed approaches differ in their basic assumptions; in particular, logit model is based on the Random Utility Maximization theory, Decision Tree extracts significant patterns directly from the data, and the visual approach is a descriptive method which does not require any statistical assumption. Therefore, each approach faced the problem from a different perspective, whereby many results were obtained enriching the analysis about switching intentions towards car sharing. The logit models and Decision Trees were calibrated and validated using the same dataset, in order to compare their results in terms of variables effect and prediction performances. Moreover, each model considered the switch from the mode currently adopted by respondents and car sharing, in order to analyse variables affecting the choice to perform the same trip chain in the future. In this way, unlike previous works, variables affecting the switching intentions were mode specific, leading to a deeper understanding of the relationship between each traditional means and car sharing.

Results of the proposed approaches were complementary and others were common. In particular, the visual approach provided preliminary descriptive analysis on the effect of trip attributes. Moreover, logit models were helpful to understand the effect of different exogenous variables and to derive further information to forecast the consequences of the introduction and diffusion of car sharing on future scenarios, e.g. by using trip switching probabilities. On the other hand, results from Decision Trees were used to identify the non-continuous effects of different variables, by estimating specific thresholds for each factor. Specifically, the analysis of trip attributes that can promote or avoid the shift was helpful to outline the relationship of car sharing with traditional travel means, defining the best ambit of use of each mode.

All three models pointed out that reducing the cost of car sharing could induce the shift from private cars. Moreover, the same effect can be strengthened by increasing the cost of driving a private vehicle, reducing the duration of the trips by at least 3 minutes or decreasing the walking time to reach the shared car. Car sharing can substitute private car for trips shorter than 14 kilometres, even starting from outside the city and with a destination within the city. However, potential members are willing to walk up to 6 minutes to reach the shared vehicle. As regards public transport, in general, low potential substitution rates were found for urban trips, i.e. with short distance and long duration, in particular for trips shorter than 10-18 kilometres. Furthermore, in order to avoid the shift towards car sharing, the cost of public transport trips should be lower. On the other hand, waiting time at the transit stop is a factor that affects switching intentions, in particular, positive switches were predicted if the waiting time was greater than 3 minutes, moreover potential car sharers are willing to pay up to 0.8 € to avoid 4 minutes of waiting time. Furthermore, shifts might occur if the in-vehicle travel time on car sharing was lower than the one on public transport. Therefore, in order to prevent the switch from public transport towards car sharing, policies to maintain low fares and short waiting time (e.g. by increasing transit frequencies) should be carried out; in addition the travel speed of public transit means should be increased to compete with that of car sharing, in order to reduce potential switches. Car sharing might replace trips performed in non working days and during weekdays, by employees and students. In addition, car sharing was found not to be suitable for very short trips, in particular, for travel distances shorter than 2 kilometres and with a duration lower than 30 minutes, since these type of trips are usually performed by bike or walking. In particular, trips up to 300 meters long are carried out on foot, whereas the maximum distance by bike turned out to be 1.4 kilometres. Moreover, reducing the cost of car sharing and the walking distance to reach a vehicle might induce the shift, not only from private car, but also from bike and walking. However, bikers are willing to walk up to 9 minutes and they might decide to switch if they could reduce this time of at least 5 minutes, if compared to the walking time to reach their bikes.

In addition, alternative mobility scenarios were generated using the estimated models, in order to quantify the effect of this service on modal split and parking space. In particular, logit models were applied to obtain the number of predicted trips on car sharing. Moreover, the impact of car sharing on public space was analysed through the definition of parking events, i.e. a parking space that is occupied by a vehicle whose trip was switched to car-sharing; following this perspective, the calibrated modal switching logit model was applied to estimate the number of avoided parking events. Moreover, since each respondent reported the type of parking location (on-street, public parking or garage), the specific parking time and geo-localized places, it was possible to assess the kind of effect of shifting trips, considering origins and destinations, separately. Specifically, the first considered scenario was the base observed scenario, which derived from the analysis of the sampled data obtained from the mobility survey. The second one was the growth scenario, in which no exogenous policy measures were carried out, and which was supposed to occur after a wide diffusion of car sharing among Turin inhabitants. The third group of scenarios was generated by varying the cost of car sharing trips and the parking fares, which are the two factors that public authorities can manage by carrying out specific interventions on the parking fares in the city, which might indirectly affect the cost of car sharing. For each combination of these two factors, modal switching models were applied to estimate the number of diverted trips to car sharing. After that, the scenario which maximizes the number of switching trips from private car and minimizes those from public transport, bike and walking was selected as the optimal scenario. For each of the two alternative scenarios, the distribution of parking events was analysed and mapped for each Traffic Analysis Zone.

Results indicated that car sharing can effectively reduce the number of car trips. Sensitivity analysis suggested that, in order to maximize the difference between trips diverted from private car and those from the other base modes, the cost of car sharing should not change, but parking fares should be increased. The optimal selected scenario allowed obtaining the highest value of diverted trips from private car. Moreover, the number of car sharing predicted trips was similar to the one to bike and walking. A positive net impact in terms of avoided parking events was observed in both the two alternative scenarios. However, the spatial distribution was quite different; in particular, the optimal scenario produced a greater number of positive parking events for the city of Turin, where the car adoption is affected by the parking cost.

In conclusion, estimating and analysing travel demand of car sharing is important to evaluate its impacts, in particular on existing travel modes. From this perspective, the proposed analysis can provide sound basis to policy makers and local authorities, who have to decide whether to address public resources to promote car sharing and to provide travellers with a range of mobility options which can accommodate all their mobility needs. In particular, the definition of the best ambit of use of each travel means, namely the characteristics of trips which best fit to a specific mode can be useful to clarify how car sharing can be effectively introduced to maximize its positive effects, by promoting the shift from private car and avoiding the switches from other sustainable modes. Moreover, the developed analysis can be helpful for policy makers to understand the effect of car sharing on modal split by testing different policies on car sharing fares and parking cost. Specifically, policy makers can properly address financial resources, since concession to car-sharing operators are often based on parking permissions; on the other hand, sound basis were provided to define reallocation strategies of saved spaces in urban planning.

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Appendix A. Surveying activities developed within the DEMONSTRATE project

A.1 Summary and description of the survey

A.1.1 Introduction

The aim of the survey was multiple: to record information about trips performed by respondents in the 24 hours before the interview, to ask specific questions about a particular trip among those previously reported, to conduct Stated-preferences experiments on this trip, and to register socio-economic information of the interviewed.

The survey was implemented under the DEMONSTRATE project ("Modal diversion, co-modality and technology applications in passenger transport systems"), which was partly financed through a "Ricerca dei Talenti" grant from Fondazione CRT (Turin, Italy). The entire structure and the sampling plan of the survey were designed by professor Marco Diana and his research group at Politecnico di Torino (Turin, Italy). Then, the survey was implemented in an online platform by an external firm. Before the definitive administration, several preliminary versions were checked through pilot studies, which were administered to a small sample of interviewees. Respondents' answers were deeply analyzed to test the correct comprehension of questions, thus avoiding ambiguous results. The duration of the whole survey was about 10 minutes.

The final version of the questionnaire was implemented in the Turin Metropolitan Area, made by the Turin municipality, with about 800.000 inhabitants and 23 traffic analysis zones, and the municipalities surrounding the city, with about 544.000 inhabitants and 31 traffic analysis zones. The same survey was administered through both CATI (Computer Assisted Telephone Interviewing) and CAWI (Computer Assisted Web Interviewing) protocols, for 7 days a week in three different 4-weeks periods, to control for seasonal effects, to the following samples:

1. September-October 2016 (1526 respondents);
2. February 2017 (1460 respondents);
3. June 2017 (1480 respondents).

In this way, 4466 interviews were collected. In particular, telephone interviews were performed from 16:45 to 20:45, each day. On the other hand, web interviews were carried out by sending a web link to potential respondents, who could access the questionnaire from every personal device; each link was labelled with a unique personal code, in order to avoid multiple answers by a single interviewee. Unlike previous works, the survey was administered to a representative sample of the population living in the study area, in order to obtain generalizable results.

The following paragraphs contain a brief description of the sampling procedure and the structure of the survey; after that, the English translation of the final version of the technical document is attached, which reports all the questions, the design of the sample and of the Stated-preferences experiments.

A.1.2 Sampling procedure

In order to obtain a representative sample of the population of interest, a stratified random sampling technique was adopted. Following this approach (Ortuzar and Willumsen, 2011), the population is divided into homogeneous strata, respect to predefined stratifying variables, using a priori information on the characteristics of the universe. After that, random sampling is performed inside each stratum, adopting the same sample rate. In this way, the correct proportions of each stratum in the final sample are obtained, thus ensuring the representativeness of each class of the population. For the current survey, the following five stratifying variables were selected; in particular, the first four variables are related to characteristics of the respondent and the last one is related to the completeness of the questionnaire:

1. Gender of the interviewee, with two classes (male and female);
2. Age of the interviewee, which was divided into nine classes (18-20, 21-24, 25-29, 30-34, 35-44, 45-54, 55-64, 65-74, 75 years and more);
3. Occupational status of the interviewee, with three classes: employed people (employees and self-employed) belonging to the workforce, unemployed people belonging to the workforce, and economically inactive people (e.g. students and pensioners);
4. Traffic analysis zone where the interviewee lives. In this case, 54 classes were considered: 23 zones belonging to the Turin Municipality, and 31 zones corresponding to municipalities belonging to the Turin Metropolitan Area (excluding the municipality of Turin);
5. Since each interviewee was allowed to fill in only some parts of the survey, this stratifying variable checks which sections were completed.

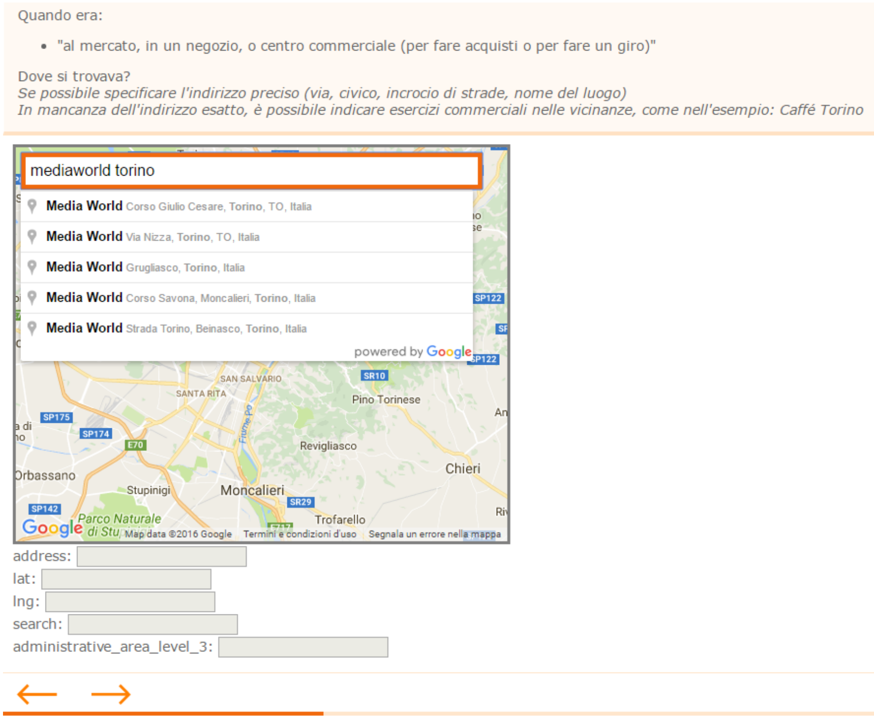
For the traffic analysis zones within the Municipality of Turin, data about the distribution of the population according to gender and age were obtained from the Municipality of the city (Comune di Torino, 2007). Whereas, the corresponding information for the zones surrounding the Municipality of Turin, were derived from the National Census carried out in 2011 by Italian National Institute for Statistics (ISTAT – Istituto Nazionale di Statistica) (ISTAT, 2011). Following the designed method for the sampling procedure, thresholds were fixed for each stratum, which represent the minimum number of observations for each combination of the five stratifying variables.

A.1.2 Questionnaire

The survey consisted of six sections, which were presented to the interviewee with the same order reported in the following: Introduction, Travel diary, Focus on a specific trip chain, Attitudinal survey, Stated-preferences experiments, and Socio-economic characteristics. Moreover, for each interview, the implemented system automatically stored the unique identification code, the type of the interview (CATI or CAWI), the code of the interviewer (if CATI were used), the date, and the starting and ending time of the survey.

A. INTRODUCTION

First, a short introduction was shown, containing a brief description of the survey, and information about its aims and who designed it. After that, preliminary screening questions were posed, in order to understand to which stratum the interviewee belongs. These questions considered four out of five stratifying variables. In particular, the respondent was asked to indicate her gender, age, dwelling zone, and occupational status. In particular, the following working activities were presented: entrepreneur, manager or officer, employee or trade employee, worker, teacher, salesman, artisan or retailer, student, homemaker, pensioner, waiting for first employment or never worked, and unemployed. The dwelling zone of the interviewee and each activity location in the survey were collected by embedding the Application Program Interface (API) provided by Google Maps (Google LLC, 2019a). In this way, the respondent could both digit a generic location (e.g. the municipality where she lives) or a specific address (the one of her house or the one near a Point Of Interest) or indicate a position using an indicator. Figure 43 and Figure 44 show the windows embedding Google Maps API and the options given to the respondent to select an activity location or a residential address.



While you were:

- “shopping or visiting a shopping center”

where were you?
Please indicate the specific address (street, street number, street crossing, name of a Point Of Interest)
You can also write the name of a close store, e.g.: Caffé Torino

Figure 43. Screen snapshot of the original window showing the question about dwelling zone of the respondent (in Italian); English translation in the box below

In which municipality do you currently live?
Please indicate the specific address (street, street number, street crossing, name of a Point Of Interest)
You can also write the name of a close store, e.g.: Caffé Torino

Figure 44. Screen snapshot showing the options to report dwelling address or location (in Italian); English translation in the box below

B. TRAVEL DIARY

The first question of this section was related to the monthly frequency of use of the following transport modes: bike, bike sharing, motorbike, car as a driver, car sharing, car as passenger, taxi, school/company bus, urban bus or tram, metro, suburban bus and train. For each travel means the interviewee had multiple possible choices: more than three times per week, from one to three times per week, less than once a week and never.

Then, information about trips and related activity patterns spanning over the 24 hours before the interview were collected, through the workflow represented in Figure 45. Following the proposed approach, each respondent was asked to focus on the activities that she carried out, instead of trips; since users are more familiar with reporting her activities, results on related travel characteristics were found to be more accurate (Ampt and Ortúzar, 2004). Furthermore, each activity location was entered using Google Maps API, in order to automatically estimate travel distances and durations, covered using the reported travel mode. Each reported activity was coded using a progressive number, represented by "n" in the diagram. In this survey, the following types of activities were considered:

1. Staying at home;
2. Working (in the usual place of work);
3. Business (working not in the usual place, e.g. in a client's office or for a meeting);

4. Working to carry loads or passengers (e.g. truck driver or delivery man);
5. Studying at school or university;
6. Medical consultations or treatment;
7. Eating and or drinking (unless the main purpose was to meet friends or relatives);
8. Grocery shopping or visiting a shopping centre;
9. Taking away or picking up people (for example, taking a child to school);
10. Other discretionary and recreational activities (all types of entertainment or sport, clubs, and voluntary work, non-vocational evening classes, political meetings).
11. Visiting friends, relatives (both at someone's home or a pub, restaurant);
12. Travelling (alone or with someone else);
13. Taking a stroll;
14. Other activities to be specified manually.

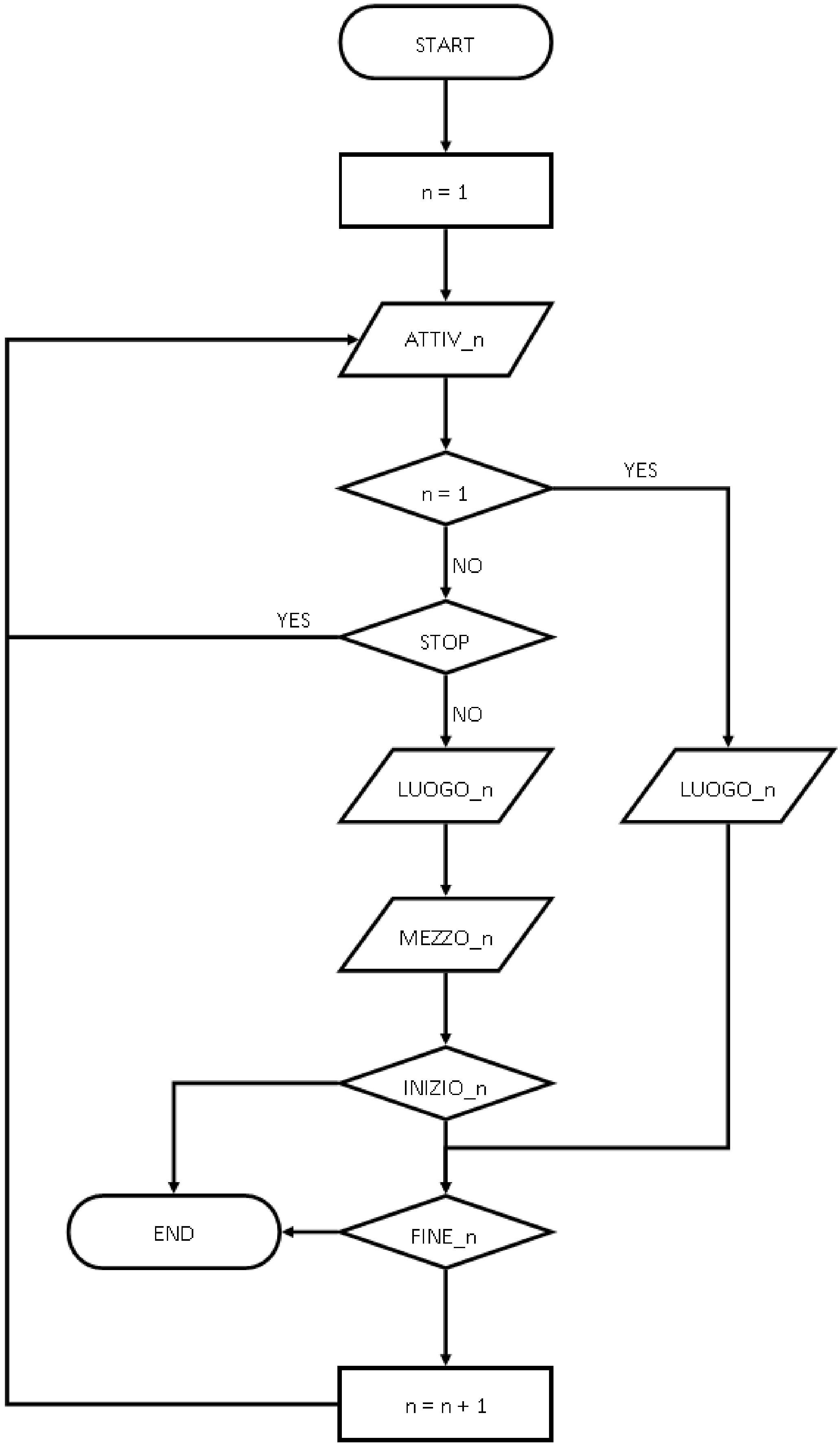


Figure 45. Flow diagram showing the structure of the section B of the survey

For the first requested activity (n is equal to 1), the respondent was asked to report what she was doing 24 hours before the interview (ATTIV_n) and the location of that activity (LUOGO_n). In the latter case, a window embedding Google Maps API was presented, like for the previous question about the residential address. After that, the interviewee had to indicate the time when that activity ended (FINE_n). If she had been performing the same previously described activity in the same place, for the 24 hours before the interview, the respondent did not carry out any trip. Therefore, the system automatically jumped to the last section of the survey, about socio-economic characteristics of the traveller. Otherwise, the counter was incremented by 1, and the interviewee was asked to report the activity that she carried out immediately after the first one (ATTIV_n). Then, since the user might not have a correct definition of activity from a travel perspective, she was requested to confirm or not whether she carried out any intermediate stops from the two previously registered activities (STOP). In this way, the reliability of the sequence of activities was ensured. If the answer was negative the interviewee could indicate the place of the last activity (LUOGO_n). Otherwise, if the answer was positive, i.e. the respondent had performed an intermediate stop, a question about what she did at the stop was posed again (ATTIV_n), overwriting the previously reported activity. Thus, the flow of activities was restored. Then, the respondent had to declare again if there were further intermediate stops (STOP), and, in case of a negative outcome, she was asked to report the related activity location (LUOGO_n). After that, she had to list all the travel modes that she adopted to reach that activity location (MEZZO_n). In particular, the respondent had to declare the means by following the real order of usage and by inserting the mode each time that she used it (i.e. if she used an urban bus twice, she had to add it two times). For this question, the following transport means were considered:

1. Walking for at least five minutes;
2. Personal bike;
3. Bike sharing;
4. Motorbike;
5. Car as driver;
6. Car sharing;
7. Car as passenger;
8. Taxi;
9. School/company bus;
10. Urban bus or tram;
11. Metro;
12. Suburban bus;
13. Train;
14. Airplane;
15. Ship.

Then, the interviewee was asked to report the time when she began the last activity (START_n). If she indicated that, at the time of the interview, she was still travelling, she had to write the estimated arrival time. Moreover, the system ended the current section, and it automatically presented questions of the next section of the survey. Otherwise, the respondent had to indicate when she finished that activity (FINE_n). After that, the counter was increased by 1, and the flow of questions was restarted (ATTIV_n).

In this section, the system automatically calculated and stored the travel distance by car between two activity locations. The estimation was performed querying Google Maps Distance Matrix API (Google LLC, 2019b) and Google Maps Directions API (Google LLC, 2019c).

C. FOCUS ON A SPECIFIC TRIP CHAIN

In this section and the following ones, except for the last one, questions were targeted on a specific trip chain (also called macro-trip, in the following), which was randomly selected among those listed in the previous section. A specific procedure to define the trip chain was developed in order to increase the degree of realism for the respondent related to urban transport modes under analysis. First, two kinds of trips were excluded from the draw a priori: those longer than 50 km and or performed outside the study area. If all the reported trips had one or both of these characteristics, then the interviewee had to face only questions in the last section. Otherwise, one trip was drawn among the remaining ones. After that, the selected trip was merged by preceding and or following trips, if interposed activities lasted less than 30 minutes. In this way, a trip chain containing shorter activity durations was automatically selected for further analysis rather than the individual trip. Though this approach respondent could focus on a trip chain that makes sense to her, better matching the common understanding of a trip, beyond the technical definition adopted in transport field (i.e. the movements between two activity locations) (Diana, 2010, 2008). This methodology produced more accurate and reliable results (Ortuzar and Willumsen, 2011).

Once the macro-trip was defined, the system stored attributes of the trip chain, such as total travel duration, location of the starting and ending points, activities performed at the origin and the destination, and adopted travel means. Then these information were used to calculate travel times and distances on car, public transport and walking, by querying Google Maps Distance Matrix API (Google LLC, 2019b) and Google Maps Directions API (Google LLC, 2019c).

After that, the respondent was asked to identify the transport mode on which she travelled for the majority of the trip chain duration. Moreover, detailed questions were posed about the macro-trip also considering adopted modes. The interviewee had to indicate the frequency of that trip chain, the number of passengers (excluding other public transport users), if she had to carry any loads, luggage, strollers or animals, and which activities she performed during the travelling (such as studying, reading a book, listening to the music, watching a video, phoning). Moreover, she was asked to report the walking time to reach a travel mode. The following questions differed according to all transport means that the respondent adopted:

1. For private car, the traveller had to specify the vehicle fuel type, where it was parked both at the origin and at the destination of the trip, parking cost, toll and who bore the costs;
2. For a car passenger, the same questions for car drivers were posed and, in addition, the following information were requested: waiting time for the vehicle and who drove the vehicle;
3. For public transport, the interviewee had to indicate the waiting time at transit stops, the type of ticket or subscription, and the related cost;
4. For a car sharing user, questions were posed about the car sharing operator, the cost of the trip, who bore that cost, membership duration and which travel means she used before car sharing;

5. For taxi, the respondent was asked to report the waiting time, the adopted booking system, cost and who bore it;
6. A bike sharing user had to answer questions about membership duration and which travel means she used before bike sharing.

D. ATTITUDINAL SURVEY

In this section, attitudinal questions focusing on the selected trip chain were posed to the respondent. First, she had to list all the different travel modes that she used in the past to complete the same macro-trip. Then the interviewee was asked to report all the transport means that she intended to adopt in the future to perform the same trip chain. After that, she had to indicate possible accidents that happened during the trip, such as stopped vehicle because of traffic congestion, car accident, wrong and dangerous actions of a driver, bikers or pedestrian, unusual delay of public transport, or missing the bus or train. In addition, the respondent was requested to state her satisfaction levels through a valence and activation scale (Ettema et al., 2011, 2010).

E. STATED-PREFERENCES EXPERIMENTS

In this section, in order to investigate mode switching attitudes for the chained trip, Stated-preferences experiments were carried out, using the previous trip chain as a unit of analysis. Adopting this most disaggregated level, rather than a person level, allowed an easier insertion in transportation models (Diana, 2010). Furthermore, focusing on an actually performed trip increased the realism of users' choices and, therefore, the reliability of results (Hensher, 2010; Train and Wilson, 2008). This is particularly challenging if the interview is not familiar with the alternative mode (Diana, 2010), as in the case of recently introduced transport means, like car sharing.

The present work followed the approach proposed by Diana (Diana, 2010), who focused on modal diversion rather than mode choice, in order to better face the forecasting of new transport modes. Moreover, the general framework of implemented Stated-preferences experiments was based on a modified version of the survey developed by Diana (Diana, 2010, 2008). The typical structure of each question is reported in Figure 46. In particular, the respondent had to declare her preference between two transport modes, assuming that she had to complete the same selected macro-trip again in the future. The first mode was the already used one (in case more than one was used, the mode used for most of the time to complete all trips composing the trip chain was automatically selected). The latter was one alternative switching mode among the following six: car as driver, car sharing, public transport, bike, bike sharing, and a kind of shared taxi in which users share the ride with other passengers booking their trip in advance. Therefore, each interviewee had to face six experiments, one for each of the six alternative modes. In each experiment she had to choose one mode between the mode currently adopted and the alternative one. Whenever the current mode was equal to one of the six alternative switching modes, then the corresponding Stated-preferences experiment proposed the same mode for the two alternatives, which had however different attributes. For the experiment implementation an orthogonal fractional design (Ortuzar and Willumsen, 2011) was developed, with 3 levels for each of the 4 trip attributes, generating 18 questions divided into 3 blocks. In this way each respondent had to face 6 experiments, one for each alternative mode.

Figure 46 shows that, unlike traditional approaches, the two alternatives are not presented in a symmetric way, by showing cards with attributes of means, since the interviewee had not to choose the best alternative (like in mode choice analysis), but she had to focus on the switching from an experienced option to a new one (like in modal diversion analysis). Thus, the adopted binary choice situation simulated the mental process of the user's choice (Diana, 2010). Furthermore, since one of the aims was to assess which trip characteristics are suitable for each travel mode, sentences presented in Stated preference experiments were worded in order to be sure that the respondent can effectively perform that trip chain with the shown mode. For example, whenever the SP experiment has "car sharing" as alternative mode (like in Figure 46) the following sentence was added as a precondition: "imagine that you are a member of a car sharing service which is suitable for your trip and you can use it".

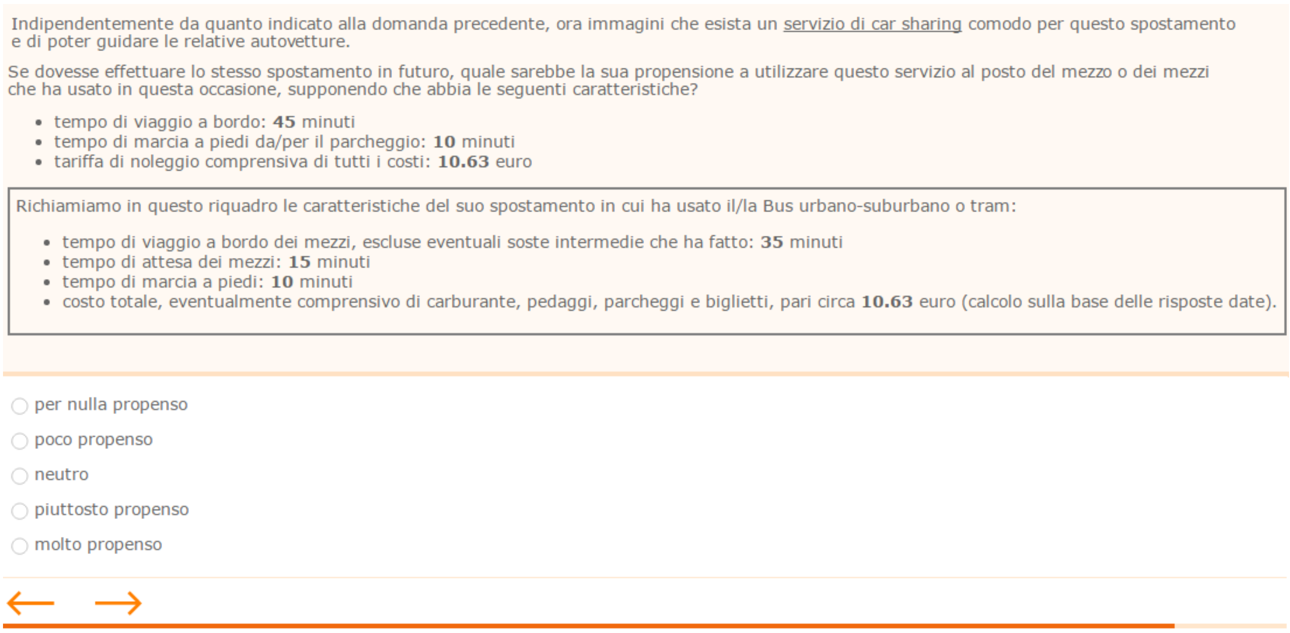
Furthermore, unlike other surveys, the interviewee had to express her propensity to shift to the alternative mode using an ordinal scale, rather than declaring a cut-off choice. In particular, answers were elicited on a 5 points scale ranging from "I am not at all inclined to use the switching mode" to "I am strongly inclined to use the switching mode", going through a neutral point. This approach is consistent with the design of questions, since it would be difficult for the respondent to answer to the switching choice between a known mode to a new one, by declaring a clear choice (Diana, 2010).

Moreover, in order to increase the realism and to obtain reliable answers, in each experiment, beyond the attributes of both the current and of the switching mode, a reminder displayed information about the selected trip chain. In particular, observing Figure 46, one can note the main mode indicated in the Revealed Preferences part of the survey and related trip attributes were shown.

For each of the six experiments, the following four attributes were considered, which were different according to the mode under analysis:

- in-vehicle travel time;
- walking time to reach the public transit stop and waiting time at the stop (for public transport modes);
- walking time to reach the parked vehicle (for car, car sharing and bike sharing);
- travel costs for the whole trip chain. In particular, public transit ticket or subscription (for public transport modes), tolls, fuel and parking fares (for car), other fares (for car sharing, bike sharing and shared taxi) were considered.

Attributes of the current mode were calculated by directly considering the corresponding answers on the relevant items. Whereas attributes of each of the six switching modes were rather estimated by processing information on the trip chain (e.g. geographical locations, departure/arrival times) through Google Maps APIs, additionally integrating information related to public transit operations, car sharing and bike sharing services (namely, fares and subscription costs), along with average cost of fuels. In this way, attributes of alternatives were very close to the attributes of the corresponding macro-trip carried out with the alternative mode. Therefore the experiment is based on a real trip with realistic characteristics of the switching mode, thus providing sound basis for the realism and reliability of users' switching intentions.



Indipendentemente da quanto indicato alla domanda precedente, ora immagini che esista un servizio di car sharing comodo per questo spostamento e di poter guidare le relative autovetture.

Se dovesse effettuare lo stesso spostamento in futuro, quale sarebbe la sua propensione a utilizzare questo servizio al posto del mezzo o dei mezzi che ha usato in questa occasione, supponendo che abbia le seguenti caratteristiche?

- tempo di viaggio a bordo: **45** minuti
- tempo di marcia a piedi da/per il parcheggio: **10** minuti
- tariffa di noleggio comprensiva di tutti i costi: **10.63** euro

Richiamiamo in questo riquadro le caratteristiche del suo spostamento in cui ha usato il/la Bus urbano-suburbano o tram:

- tempo di viaggio a bordo dei mezzi, escluse eventuali soste intermedie che ha fatto: **35** minuti
- tempo di attesa dei mezzi: **15** minuti
- tempo di marcia a piedi: **10** minuti
- costo totale, eventualmente comprensivo di carburante, pedaggi, parcheggi e biglietti, pari circa **10.63** euro (calcolo sulla base delle risposte date).

- ○ per nulla propenso
- ○ poco propenso
- ○ neutro
- ○ piuttosto propenso
- ○ molto propenso

Independently on what you reported in the previous question, please imagine that you are a member of a car sharing service which is suitable for your trip and you can use it.

If you had to perform the same trip again in the future, what would be your propensity to use the following mode with travel characteristics explained below, instead of the mode or modes that you currently adopt?

- in-vehicle travel time: **45** minutes
- walking time to reach the parked car: **10** minutes
- total trip cost: **10.63** euros

In this box, travel characteristics of the trip carried out by urban bus are recalled:

- in-vehicle travel time, excluding intermediate stops: **35** minutes;
- waiting time: **15** minutes
- walking time: **10** minutes

- ○ I am not at all inclined to use the switching mode
- ○ I am not very inclined to use the switching mode
- ○ Neutral
- ○ I am slightly inclined to use the switching mode
- ○ I am strongly inclined to use the switching mode

Figure 46. Screen snapshot of the original version of a typical question of Stated-preferences experiments presented to a respondent (in Italian); English version in the box below

F. SOCIO-ECONOMIC CHARACTERISTICS

In this last section of the survey, questions about socio-economic characteristics of both the respondent and her household were posed. First, the interviewee was asked to indicate to which sector her job belonged (such as agriculture, manufacturing, trade, services, public administration) and the highest level of education that she had (no studies, primary school, middle school, high school, university degree or doctorate). Moreover, the respondent was requested to report if she had a driving license, a private park near home and or near the working or studying place, a subscription to public transport, car sharing or bike sharing, and how long she was a member of the last two services. On the other hand, questions about the user's household were related to the number of household members, children, employees, driving licensed people, underage children, owned cars, owned motorbikes, and the range of monthly household income.

A.2 Technical documentation related to the call for tenders to choose the surveying firm

In the following pages, an English translation of the technical documentation that was made available to those surveying firms interested in making an offer to the call for tenders to implement the survey is presented. Indeed, it contains a number of attachments that spell out some technical characteristics of the required field activity, including the stratified sampling plan with the required minimum number of interviews in each stratum, the complete questionnaire, the structure of the SP experiment, the algorithm to compute the values of the alternatives for different levels and different attributes in the SP experiments, the related experimental design,

DEMONSTRATE project

Modal diversion, co-modality and technology applications in passenger transport systems

Survey on mobility and modal diversion propensity in the Turin metropolitan area

<u>Technical Document</u>

Final Version

25th November 2016

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Contact: Marco Diana, marco.diana@polito.it

A.2.1 General and technical rules

Art 1. Aim of the activities

The aim of the activity is to design and implement a survey about the trips shorter than 50 kilometers performed by the adult persons living in the Turin metropolitan area. Through this survey all the trips carried out by respondents in the 24 hours before the interview are collected, detailed questions are posed on a specific trip. Moreover, stated-preferences experiments are asked to the respondents and their socio-economic characteristics are registered.

The activity includes the development of the system to collect data, following the questionnaire and the technical specifications reported in Attachment 2, and the data registration.

Art 2. Main characteristics of the survey

In order to improve the data collection activities the survey must be implemented through both CATI (Computer Assisted Telephone Interviewing) and CAWI (Computer Assisted Web Interviewing) protocols.

[Omissis]

Art. 5. Sampling procedure and sample size

The survey must be administered to a stratified sample of the population living in the Turin metropolitan area, which is divided into sampling zones following the procedure in Attachment 1. The sample contains observations obtained both using both CATI (Computer Assisted Telephone Interviewing) and CAWI (Computer Assisted Web Interviewing) protocols. The characteristics of the sample must observe the requirements reported in Attachment 1.

A collected observation can belong to the sample if the variable CAMPION is equal to 1 (see attachment 2). Moreover, the total number of collected observations could be greater than the number of observations belonging to the sample, since:

- There might be uncompleted observation, due to a possible interruption of the interview (CAMPION is equal to 4);
- Further interviews might be collected through CAWI protocol, even if they do not belong to the sample (CAMPION is equal to 2 or 3).

These observations in excess cannot be considered to reach the final required sample size. However, among observations in excess, some of them with CAMPION equal to 3 could become part of the final sample (CAMPION equal to 1), following the stratification of the sample requested in Attachment 1.

Art.6. Criteria to define if an interview is complete

A generic observation belongs to the final sample (CAMPION equal to 1) if and only if the related interview contains complete information in three or six sections of the questionnaire. Each section is considered complete if the following criteria are observed:

- For section A and B: all the questions must contain an answer and variables GOO_D_n must have been created (see Attachment 2)
- For section C: at least questions MODO, ORIGINE, DESTINAZIONE, detailed questions about the most used travel mean, and half of the remaining questions must be answered. Moreover variables GOO_TAU, GOO_TTP, GOO_TPI, GOO_DAU e GOO_DPI must have been created (see Attachment 2).
- For Sections D, E and F: at least 75% of the questions in each section must be answered.

Art.7. Tasks

Tasks to perform the travel survey are described in the following.

Plan of activities. A plan of activities must be provided to the customer within 10 days after receiving the job assignment. The plan of activities must contain the sampling plan. Both of them will be approved by the customer. In this phase, revisions could be requested in order to improve the efficiency of the survey. The assignee must provide an automatic system to check and correct irregular collected data (e.g. incongruous codes, questions without answers), in order to obtain reliable data. This system must automatically assign also specific codes for questions without answers, “legitimate skips”, etc. (see Attachment 2). This system must be approved by the customer.

Survey implementation. The survey (Attachment 2) must be implemented in the same software for both CATI and CAWI protocols. During this phase, the assignee must work together with the customer, in order to ensure a correct understanding of the answers, to maximize the effectiveness of the survey. The assignee must design the appearance and graphical elements of the survey. In the case of CAWI protocol, the assignee must provide a system to ensure that the survey is answered only once by the same interviewed. This phase must end within 2.5 months after the job assignment.

Pilot studies, interviewers briefing and selection of the sampled population. The assignee must test the survey through pilot studies, by administering the questionnaire to at least 60 persons (30 CATI). The customer can change the survey, without modifying its length. Before administering the survey, the assignee must have a briefing with the interviewers, in order to show them the questionnaire and to provide them with all the information to carry out the survey. Interviewers must avoid unexpected interruptions of the survey. The assignee must select the sample with the requested characteristics (see Attachment 1). All the activities must be completed within 6 months after the job assignment.

Survey administration. Interviews obtained through CATI protocol must be stored in real time. Each phone number must be contacted at least 5 times, in different hours and days, before being discarded and substituted with another phone contact. The assignee must inform immediately the customer about possible problems during the interviews. The assignee must supervise the interviewers.

Coding, geo-localization and data cleaning. The assignee must code and clean the collected data. Residential locations, origins and destinations of trips must be coded following the distribution of zones provided by the customer. In particular, Turin municipality is divided into 23 zones, whereas a zone is assigned to each of the municipalities surrounding the city. The assignee must provide complete and correct addresses (e.g. in case of missing house number, an alternative must be provided). The final number of interviews does not include discarded observation after the data cleaning phase. In this phase, the assignee must send all the notes added by the interviewers, in order to define a correct solution to encode the answers.

Data storing and delivery. Collected data must be stored in text files. A separated file with the contacted phone numbers (CATI) and e-mail addresses (CAWI) must be provided. The files must be sent within 7.5 months after the job assignment.

Final report. The assignee must provide a final report, containing the sampling plan, which must be organized following the four tables in Attachment 1 (with absolute and percentage values). The final report must be sent to the customer within 8 months after the job assignment.

A.2.2 Attachment 1. Sampling plan

The collected observations could belong to the final sample (CAMPION equal to 1) or they could be in excess (CAMPION equals to 2, 3 or 4). Only the formers must observe the ratio and thresholds for each of the following classes.

The following five stratifying variables are defined:

- Gender of the interviewee, with two classes (male and female);
- Age of the interviewee, which was divided into nine classes (18-20, 21-24, 25-29, 30-34, 35-44, 45-54, 55-64, 65-74, 75 years and more);
- Occupational status of the interviewee, with three classes: employed people (employees and self-employed) belonging to the workforce, unemployed people belonging to the workforce, and economically inactive people (e.g. students and pensioners);
- Traffic analysis zone where the interviewee lives. In this case, 54 classes were considered: 23 zones belonging to the Turin Municipality, and 31 zones corresponding to municipalities belonging to the Turin Metropolitan Area (excluding the municipality of Turin);
- Since each interviewee was allowed to fill in only some parts of the survey, TERMINE variable checks which sections were completed (2 classes: 1, and from 2 to 4). For observations belonging to the final sample, TERMINE must not be equal to 5 or 6.

For the traffic analysis zones within the Municipality of Turin, data about the distribution of the population according to gender and age were obtained from the Municipality of the city (Comune di Torino, 2007) (Table 4). Whereas, the corresponding information for the zones surrounding the Municipality of Turin, were derived from the National Census carried out in 2011 by Italian National Institute for Statistics (ISTAT – Istituto Nazionale di Statistica) (ISTAT, 2011) (Table 1, 2 and 3).

The final sample must observe the following conditions:

1. All stratum labelled with green in tables form 1 to 4 must be represented by at least 1 observation;
2. All stratum labelled with pink in tables form 1 to 4 must be represented by at least 1 observation;
3. The percentage of observations with TERMINE = 1, 3 or 4 must be at least 80%;
4. The percentage of observations with TERMINE = 1 must be at least 75%;

Table 1. Distribution of adult males (2011)

Maschi	18-20 anni	21-24 anni	25-29 anni	30-34 anni	35-44 anni	45-54 anni	55-64 anni	65-74 anni	75 anni e più	**18 anni e più**	15 anni e più
Alpignano	0.02%	0.03%	0.03%	0.04%	0.09%	0.10%	0.10%	0.07%	0.05%	**0.54%**	0.54%
occupato											0.29%
cerca occupaz.											0.03%
non forze lav.											0.23%
Baldissero Torinese	0.00%	0.01%	0.01%	0.01%	0.02%	0.02%	0.02%	0.02%	0.01%	**0.12%**	0.12%
occupato											0.07%
cerca occupaz.											0.00%
non forze lav.											0.05%
Beinasco	0.02%	0.03%	0.03%	0.04%	0.11%	0.10%	0.09%	0.09%	0.07%	**0.57%**	0.57%
occupato											0.30%
cerca occupaz.											0.02%
non forze lav.											0.24%
Borgaro Torinese	0.02%	0.02%	0.03%	0.03%	0.09%	0.08%	0.07%	0.06%	0.03%	**0.42%**	0.43%
occupato											0.25%
cerca occupaz.											0.02%
non forze lav.											0.16%
Cambiano	0.01%	0.01%	0.01%	0.01%	0.04%	0.04%	0.03%	0.03%	0.02%	**0.19%**	0.20%
occupato											0.11%
cerca occupaz.											0.01%
non forze lav.											0.08%
Candiolo	0.01%	0.01%	0.01%	0.01%	0.03%	0.03%	0.03%	0.02%	0.01%	**0.17%**	0.18%
occupato											0.10%
cerca occupaz.											0.01%
non forze lav.											0.06%
Carignano	0.01%	0.01%	0.02%	0.02%	0.05%	0.06%	0.05%	0.04%	0.03%	**0.29%**	0.29%
occupato											0.17%
cerca occupaz.											0.01%
non forze lav.											0.11%
Caselle Torinese	0.02%	0.03%	0.04%	0.05%	0.12%	0.11%	0.09%	0.07%	0.04%	**0.57%**	0.57%
occupato											0.33%
cerca occupaz.											0.02%
non forze lav.											0.21%
Chieri	0.04%	0.05%	0.07%	0.08%	0.22%	0.21%	0.17%	0.14%	0.12%	**1.10%**	1.11%
occupato											0.62%
cerca occupaz.											0.05%
non forze lav.											0.43%
Collegno	0.05%	0.07%	0.09%	0.11%	0.31%	0.28%	0.25%	0.22%	0.15%	**1.52%**	1.52%
occupato											0.83%
cerca occupaz.											0.07%
non forze lav.											0.62%
Druento	0.01%	0.01%	0.02%	0.02%	0.05%	0.05%	0.04%	0.04%	0.02%	**0.26%**	0.26%
occupato											0.15%
cerca occupaz.											0.01%
non forze lav.											0.10%
Grugliasco	0.04%	0.06%	0.08%	0.09%	0.21%	0.20%	0.21%	0.18%	0.11%	**1.18%**	1.18%
occupato											0.63%
cerca occupaz.											0.05%
non forze lav.											0.51%
La Loggia	0.01%	0.01%	0.02%	0.03%	0.06%	0.05%	0.04%	0.03%	0.02%	**0.27%**	0.27%
occupato											0.17%
cerca occupaz.											0.01%
non forze lav.											0.09%
Leini	0.02%	0.03%	0.03%	0.05%	0.11%	0.08%	0.08%	0.06%	0.04%	**0.49%**	0.49%
occupato											0.29%
cerca occupaz.											0.02%
non forze lav.											0.17%

Moncalieri	0.05%	0.08%	0.10%	0.13%	0.35%	0.30%	0.28%	0.26%	0.19%	**1.74%**	1.74%
occupato											0.95%
cerca occupaz.											0.08%
non forze lav.											0.71%
Nichelino	0.05%	0.06%	0.09%	0.11%	0.31%	0.27%	0.23%	0.22%	0.14%	**1.48%**	1.49%
occupato											0.79%
cerca occupaz.											0.09%
non forze lav.											0.62%
Orbassano	0.02%	0.03%	0.05%	0.06%	0.14%	0.12%	0.12%	0.10%	0.07%	**0.71%**	0.71%
occupato											0.39%
cerca occupaz.											0.04%
non forze lav.											0.29%
Pecetto Torinese	0.00%	0.01%	0.01%	0.01%	0.02%	0.03%	0.02%	0.02%	0.01%	**0.12%**	0.12%
occupato											0.07%
cerca occupaz.											0.00%
non forze lav.											0.05%
Pianezza	0.02%	0.02%	0.03%	0.04%	0.10%	0.08%	0.07%	0.06%	0.04%	**0.44%**	0.44%
occupato											0.26%
cerca occupaz.											0.02%
non forze lav.											0.16%
Pino Torinese	0.01%	0.01%	0.01%	0.01%	0.04%	0.05%	0.04%	0.04%	0.03%	**0.26%**	0.26%
occupato											0.14%
cerca occupaz.											0.01%
non forze lav.											0.11%
Piobesi Torinese	0.00%	0.01%	0.01%	0.01%	0.02%	0.02%	0.02%	0.02%	0.01%	**0.12%**	0.12%
occupato											0.07%
cerca occupaz.											0.00%
non forze lav.											0.04%
Piossasco	0.02%	0.03%	0.03%	0.04%	0.13%	0.10%	0.08%	0.08%	0.05%	**0.56%**	0.57%
occupato											0.33%
cerca occupaz.											0.02%
non forze lav.											0.22%
Rivalta di Torino	0.02%	0.03%	0.04%	0.05%	0.12%	0.11%	0.10%	0.08%	0.06%	**0.61%**	0.61%
occupato											0.35%
cerca occupaz.											0.03%
non forze lav.											0.24%
Rivoli	0.05%	0.07%	0.09%	0.10%	0.27%	0.27%	0.27%	0.24%	0.16%	**1.54%**	1.54%
occupato											0.81%
cerca occupaz.											0.07%
non forze lav.											0.67%
San Mauro Torinese	0.02%	0.03%	0.03%	0.04%	0.11%	0.12%	0.10%	0.09%	0.06%	**0.59%**	0.59%
occupato											0.33%
cerca occupaz.											0.02%
non forze lav.											0.24%
Santena	0.01%	0.02%	0.02%	0.03%	0.07%	0.06%	0.06%	0.04%	0.03%	**0.34%**	0.34%
occupato											0.20%
cerca occupaz.											0.01%
non forze lav.											0.13%
Settimo Torinese	0.05%	0.06%	0.09%	0.10%	0.28%	0.28%	0.23%	0.20%	0.15%	**1.46%**	1.47%
occupato											0.79%
cerca occupaz.											0.07%
non forze lav.											0.61%
Trofarello	0.01%	0.02%	0.02%	0.02%	0.07%	0.07%	0.06%	0.04%	0.03%	**0.34%**	0.34%
occupato											0.19%
cerca occupaz.											0.01%
non forze lav.											0.14%
Venaria	0.04%	0.05%	0.07%	0.07%	0.19%	0.20%	0.19%	0.15%	0.09%	**1.06%**	1.06%
occupato											0.57%
cerca occupaz.											0.05%
non forze lav.											0.45%

	18-20 anni	21-24 anni	25-29 anni	30-34 anni	35-44 anni	45-54 anni	55-64 anni	65-74 anni	75 anni e più	18 anni e più	15 anni e più
Vinovo	0.02%	0.02%	0.03%	0.03%	0.09%	0.08%	0.08%	0.06%	0.04%	**0.44%**	0.45%
occupato											0.26%
cerca occupaz.											0.02%
non forze lav.											0.17%
Volpiano	0.02%	0.02%	0.03%	0.04%	0.10%	0.08%	0.08%	0.05%	0.04%	**0.47%**	0.47%
occupato											0.27%
cerca occupaz.											0.02%
non forze lav.											0.17%
Torino (comune)	0.86%	1.20%	1.72%	2.09%	5.39%	4.84%	4.03%	3.78%	3.24%	**27.15%**	27.18%
occupato			1.23%	1.72%	4.59%	4.09%	1.93%	0.40%	0.08%		14.32%
cerca occupaz.			0.19%	0.17%	0.35%	0.28%	0.15%	0.01%	0.00%		1.42%
non forze lav.			0.29%	0.21%	0.46%	0.47%	1.95%	3.37%	3.16%		11.44%
TOTALE	**1.55%**	**2.13%**	**2.96%**	**3.55%**	**9.32%**	**8.49%**	**7.32%**	**6.59%**	**5.19%**	**47.10%**	**47.24%**
occupato											**25.40%**
cerca occupaz.											**2.32%**
non forze lav.											**19.51%**

Table 2. Distribution of adult females (2011)

Femmine	18-20 anni	21-24 anni	25-29 anni	30-34 anni	35-44 anni	45-54 anni	55-64 anni	65-74 anni	75 anni e più	**18 anni e più**	15 anni e più
Alpignano	0.02%	0.02%	0.03%	0.04%	0.10%	0.11%	0.11%	0.08%	0.08%	**0.59%**	0.59%
occupato											0.24%
cerca occupaz.											0.02%
non forze lav.											0.32%
Baldissero Torinese	0.00%	0.00%	0.00%	0.01%	0.03%	0.03%	0.02%	0.02%	0.01%	**0.12%**	0.12%
occupato											0.05%
cerca occupaz.											0.00%
non forze lav.											0.06%
Beinasco	0.02%	0.03%	0.03%	0.04%	0.11%	0.11%	0.10%	0.10%	0.08%	**0.63%**	0.63%
occupato											0.25%
cerca occupaz.											0.03%
non forze lav.											0.34%
Borgaro Torinese	0.02%	0.02%	0.03%	0.03%	0.09%	0.09%	0.08%	0.05%	0.04%	**0.45%**	0.45%
occupato											0.21%
cerca occupaz.											0.02%
non forze lav.											0.22%
Cambiano	0.01%	0.01%	0.01%	0.01%	0.04%	0.04%	0.03%	0.03%	0.03%	**0.21%**	0.21%
occupato											0.09%
cerca occupaz.											0.01%
non forze lav.											0.11%
Candiolo	0.01%	0.01%	0.01%	0.01%	0.03%	0.04%	0.03%	0.02%	0.02%	**0.18%**	0.19%
occupato											0.08%
cerca occupaz.											0.01%
non forze lav.											0.09%
Carignano	0.01%	0.01%	0.02%	0.02%	0.06%	0.05%	0.05%	0.04%	0.05%	**0.31%**	0.31%
occupato											0.13%
cerca occupaz.											0.01%
non forze lav.											0.17%
Caselle Torinese	0.02%	0.03%	0.04%	0.05%	0.13%	0.11%	0.09%	0.07%	0.06%	**0.60%**	0.60%
occupato											0.27%
cerca occupaz.											0.03%
non forze lav.											0.30%
Chieri	0.04%	0.05%	0.07%	0.08%	0.24%	0.22%	0.18%	0.17%	0.19%	**1.24%**	1.24%
occupato											0.52%
cerca occupaz.											0.06%
non forze lav.											0.65%
Collegno	0.04%	0.06%	0.09%	0.11%	0.32%	0.30%	0.28%	0.26%	0.24%	**1.70%**	1.70%
occupato											0.73%
cerca occupaz.											0.08%

non forze lav.											0.90%
Druento	0.01%	0.01%	0.02%	0.02%	0.05%	0.05%	0.05%	0.04%	0.04%	**0.29%**	0.29%
occupato											0.12%
cerca occupaz.											0.01%
non forze lav.											0.15%
Grugliasco	0.04%	0.05%	0.08%	0.09%	0.22%	0.23%	0.23%	0.20%	0.17%	**1.29%**	1.29%
occupato											0.53%
cerca occupaz.											0.06%
non forze lav.											0.70%
La Loggia	0.01%	0.01%	0.02%	0.03%	0.06%	0.05%	0.04%	0.03%	0.03%	**0.28%**	0.28%
occupato											0.13%
cerca occupaz.											0.01%
non forze lav.											0.13%
Leini	0.02%	0.02%	0.04%	0.05%	0.10%	0.09%	0.08%	0.06%	0.05%	**0.51%**	0.51%
occupato											0.23%
cerca occupaz.											0.03%
non forze lav.											0.25%
Moncalieri	0.05%	0.07%	0.11%	0.13%	0.35%	0.32%	0.32%	0.29%	0.29%	**1.95%**	1.94%
occupato											0.79%
cerca occupaz.											0.09%
non forze lav.											1.06%
Nichelino	0.05%	0.07%	0.09%	0.12%	0.33%	0.27%	0.26%	0.24%	0.18%	**1.60%**	1.61%
occupato											0.67%
cerca occupaz.											0.10%
non forze lav.											0.84%
Orbassano	0.02%	0.03%	0.05%	0.06%	0.14%	0.14%	0.13%	0.11%	0.10%	**0.76%**	0.77%
occupato											0.32%
cerca occupaz.											0.04%
non forze lav.											0.41%
Pecetto Torinese	0.00%	0.00%	0.01%	0.01%	0.02%	0.03%	0.02%	0.02%	0.02%	**0.13%**	0.13%
occupato											0.06%
cerca occupaz.											0.00%
non forze lav.											0.07%
Pianezza	0.02%	0.02%	0.03%	0.04%	0.10%	0.09%	0.07%	0.06%	0.05%	**0.47%**	0.47%
occupato											0.22%
cerca occupaz.											0.02%
non forze lav.											0.23%
Pino Torinese	0.01%	0.01%	0.01%	0.01%	0.05%	0.05%	0.05%	0.04%	0.05%	**0.29%**	0.29%
occupato											0.12%
cerca occupaz.											0.01%
non forze lav.											0.16%
Piobesi Torinese	0.00%	0.00%	0.01%	0.01%	0.03%	0.02%	0.02%	0.02%	0.01%	**0.12%**	0.12%
occupato											0.05%
cerca occupaz.											0.01%
non forze lav.											0.06%
Piossasco	0.02%	0.03%	0.03%	0.04%	0.13%	0.10%	0.09%	0.09%	0.07%	**0.60%**	0.60%
occupato											0.26%
cerca occupaz.											0.03%
non forze lav.											0.30%
Rivalta di Torino	0.02%	0.03%	0.04%	0.05%	0.12%	0.12%	0.10%	0.09%	0.07%	**0.63%**	0.63%
occupato											0.28%
cerca occupaz.											0.03%
non forze lav.											0.32%
Rivoli	0.05%	0.07%	0.09%	0.10%	0.28%	0.30%	0.30%	0.26%	0.24%	**1.71%**	1.71%
occupato											0.67%
cerca occupaz.											0.08%
non forze lav.											0.95%
San Mauro Torinese	0.02%	0.03%	0.03%	0.04%	0.12%	0.12%	0.11%	0.09%	0.09%	**0.65%**	0.65%
occupato											0.28%
cerca occupaz.											0.03%

non forze lav.											0.34%
Santena	0.01%	0.02%	0.02%	0.03%	0.07%	0.06%	0.06%	0.04%	0.05%	**0.36%**	0.36%
occupato											0.15%
cerca occupaz.											0.02%
non forze lav.											0.19%
Settimo Torinese	0.05%	0.06%	0.09%	0.11%	0.29%	0.30%	0.25%	0.24%	0.22%	**1.61%**	1.61%
occupato											0.66%
cerca occupaz.											0.09%
non forze lav.											0.86%
Trofarello	0.01%	0.01%	0.02%	0.03%	0.07%	0.07%	0.06%	0.05%	0.05%	**0.37%**	0.37%
occupato											0.16%
cerca occupaz.											0.02%
non forze lav.											0.20%
Venaria	0.04%	0.05%	0.07%	0.07%	0.20%	0.21%	0.21%	0.16%	0.14%	**1.15%**	1.15%
occupato											0.48%
cerca occupaz.											0.06%
non forze lav.											0.61%
Vinovo	0.02%	0.02%	0.03%	0.03%	0.09%	0.09%	0.08%	0.06%	0.05%	**0.47%**	0.47%
occupato											0.20%
cerca occupaz.											0.02%
non forze lav.											0.25%
Volpiano	0.02%	0.02%	0.03%	0.04%	0.10%	0.09%	0.08%	0.06%	0.06%	**0.50%**	0.50%
occupato											0.21%
cerca occupaz.											0.03%
non forze lav.											0.26%
Torino (comune)	0.79%	1.18%	1.76%	2.17%	5.50%	5.12%	4.59%	4.60%	5.43%	**31.13%**	30.99%
occupato			1.11%	1.56%	4.11%	3.71%	1.57%	0.16%	0.03%		12.43%
cerca occupaz.			0.22%	0.20%	0.42%	0.29%	0.10%	0.01%	0.00%		1.48%
non forze lav.			0.43%	0.41%	0.97%	1.13%	2.92%	4.43%	5.39%		17.08%
TOTALE	**1.44%**	**2.07%**	**3.01%**	**3.67%**	**9.56%**	**9.02%**	**8.17%**	**7.69%**	**8.27%**	**52.90%**	**52.76%**
occupato											**21.61%**
cerca occupaz.											**2.55%**
non forze lav.											**28.61%**

Table 3. Distribution of the whole adult population (2011)

Maschi + Femmine	18-20 anni	21-24 anni	25-29 anni	30-34 anni	35-44 anni	45-54 anni	55-64 anni	65-74 anni	75 anni e più	**18 anni e più**	15 anni e più
Alpignano	0.04%	0.05%	0.06%	0.08%	0.20%	0.21%	0.21%	0.15%	0.13%	**1.13%**	1.13%
occupato											0.52%
cerca occupaz.											0.05%
non forze lav.											0.55%
Baldissero Torinese	0.01%	0.01%	0.01%	0.01%	0.05%	0.05%	0.04%	0.03%	0.02%	**0.24%**	0.24%
occupato											0.12%
cerca occupaz.											0.01%
non forze lav.											0.11%
Beinasco	0.04%	0.05%	0.07%	0.08%	0.22%	0.21%	0.19%	0.19%	0.15%	**1.19%**	1.19%
occupato											0.55%
cerca occupaz.											0.06%
non forze lav.											0.58%
Borgaro Torinese	0.03%	0.04%	0.06%	0.06%	0.18%	0.17%	0.15%	0.11%	0.07%	**0.88%**	0.88%
occupato											0.46%
cerca occupaz.											0.04%
non forze lav.											0.38%
Cambiano	0.01%	0.02%	0.02%	0.03%	0.07%	0.08%	0.07%	0.06%	0.05%	**0.40%**	0.41%
occupato											0.20%
cerca occupaz.											0.02%
non forze lav.											0.19%
Candiolo	0.01%	0.02%	0.02%	0.03%	0.07%	0.07%	0.06%	0.04%	0.03%	**0.36%**	0.36%
occupato											0.19%

cerca occupaz.											0.01%
non forze lav.											0.16%
Carignano	0.02%	0.03%	0.03%	0.04%	0.11%	0.11%	0.09%	0.08%	0.09%	**0.60%**	0.60%
occupato											0.30%
cerca occupaz.											0.02%
non forze lav.											0.28%
Caselle Torinese	0.04%	0.05%	0.07%	0.10%	0.25%	0.22%	0.18%	0.14%	0.11%	**1.16%**	1.17%
occupato											0.61%
cerca occupaz.											0.05%
non forze lav.											0.51%
Chieri	0.08%	0.11%	0.14%	0.16%	0.46%	0.43%	0.35%	0.31%	0.31%	**2.34%**	2.35%
occupato											1.15%
cerca occupaz.											0.11%
non forze lav.											1.09%
Collegno	0.09%	0.13%	0.17%	0.22%	0.63%	0.58%	0.52%	0.48%	0.39%	**3.21%**	3.22%
occupato											1.56%
cerca occupaz.											0.15%
non forze lav.											1.51%
Druento	0.02%	0.03%	0.04%	0.04%	0.10%	0.10%	0.09%	0.07%	0.06%	**0.55%**	0.55%
occupato											0.28%
cerca occupaz.											0.03%
non forze lav.											0.25%
Grugliasco	0.07%	0.11%	0.15%	0.17%	0.43%	0.43%	0.45%	0.38%	0.28%	**2.47%**	2.48%
occupato											1.16%
cerca occupaz.											0.11%
non forze lav.											1.21%
La Loggia	0.02%	0.02%	0.04%	0.05%	0.12%	0.10%	0.08%	0.06%	0.05%	**0.55%**	0.55%
occupato											0.30%
cerca occupaz.											0.02%
non forze lav.											0.22%
Leini	0.03%	0.05%	0.07%	0.10%	0.21%	0.17%	0.16%	0.12%	0.09%	**1.00%**	1.00%
occupato											0.52%
cerca occupaz.											0.05%
non forze lav.											0.43%
Moncalieri	0.11%	0.15%	0.22%	0.26%	0.69%	0.62%	0.60%	0.56%	0.48%	**3.69%**	3.68%
occupato											1.74%
cerca occupaz.											0.17%
non forze lav.											1.77%
Nichelino	0.10%	0.13%	0.18%	0.22%	0.64%	0.54%	0.48%	0.46%	0.33%	**3.09%**	3.10%
occupato											1.46%
cerca occupaz.											0.18%
non forze lav.											1.46%
Orbassano	0.04%	0.06%	0.10%	0.11%	0.28%	0.26%	0.25%	0.21%	0.16%	**1.48%**	1.48%
occupato											0.71%
cerca occupaz.											0.08%
non forze lav.											0.70%
Pecetto Torinese	0.01%	0.01%	0.01%	0.01%	0.04%	0.05%	0.04%	0.04%	0.03%	**0.25%**	0.25%
occupato											0.13%
cerca occupaz.											0.01%
non forze lav.											0.12%
Pianezza	0.03%	0.04%	0.05%	0.08%	0.20%	0.17%	0.14%	0.11%	0.09%	**0.91%**	0.91%
occupato											0.47%
cerca occupaz.											0.04%
non forze lav.											0.39%
Pino Torinese	0.02%	0.02%	0.02%	0.03%	0.09%	0.10%	0.10%	0.09%	0.08%	**0.55%**	0.55%
occupato											0.26%
cerca occupaz.											0.01%
non forze lav.											0.27%
Piobesi Torinese	0.01%	0.01%	0.02%	0.02%	0.05%	0.04%	0.04%	0.03%	0.02%	**0.24%**	0.24%
occupato											0.13%

cerca occupaz.											0.01%
non forze lav.											0.10%
Piossasco	0.04%	0.05%	0.07%	0.09%	0.26%	0.21%	0.17%	0.16%	0.12%	**1.16%**	1.16%
occupato											0.59%
cerca occupaz.											0.05%
non forze lav.											0.52%
Rivalta di Torino	0.04%	0.06%	0.08%	0.09%	0.25%	0.23%	0.20%	0.17%	0.12%	**1.24%**	1.25%
occupato											0.63%
cerca occupaz.											0.06%
non forze lav.											0.56%
Rivoli	0.10%	0.15%	0.19%	0.21%	0.56%	0.57%	0.58%	0.50%	0.41%	**3.25%**	3.25%
occupato											1.48%
cerca occupaz.											0.15%
non forze lav.											1.62%
San Mauro Torinese	0.04%	0.05%	0.06%	0.08%	0.23%	0.24%	0.21%	0.17%	0.15%	**1.23%**	1.24%
occupato											0.61%
cerca occupaz.											0.05%
non forze lav.											0.58%
Santena	0.03%	0.03%	0.05%	0.05%	0.13%	0.12%	0.12%	0.09%	0.08%	**0.70%**	0.70%
occupato											0.35%
cerca occupaz.											0.03%
non forze lav.											0.32%
Settimo Torinese	0.10%	0.13%	0.18%	0.21%	0.57%	0.58%	0.49%	0.44%	0.37%	**3.07%**	3.07%
occupato											1.44%
cerca occupaz.											0.16%
non forze lav.											1.47%
Trofarello	0.02%	0.03%	0.04%	0.05%	0.14%	0.14%	0.12%	0.09%	0.09%	**0.71%**	0.71%
occupato											0.35%
cerca occupaz.											0.03%
non forze lav.											0.33%
Venaria	0.08%	0.11%	0.13%	0.14%	0.40%	0.41%	0.39%	0.32%	0.24%	**2.21%**	2.22%
occupato											1.04%
cerca occupaz.											0.11%
non forze lav.											1.06%
Vinovo	0.03%	0.04%	0.05%	0.06%	0.17%	0.17%	0.16%	0.13%	0.09%	**0.91%**	0.92%
occupato											0.46%
cerca occupaz.											0.03%
non forze lav.											0.42%
Volpiano	0.03%	0.04%	0.07%	0.08%	0.20%	0.18%	0.16%	0.11%	0.10%	**0.96%**	0.97%
occupato											0.49%
cerca occupaz.											0.05%
non forze lav.											0.43%
Torino (comune)	1.65%	2.38%	3.48%	4.26%	10.89%	9.96%	8.62%	8.37%	8.67%	**58.28%**	58.17%
occupato			2.35%	3.28%	8.70%	7.80%	3.50%	0.56%	0.12%		12.43%
cerca occupaz.			0.41%	0.37%	0.77%	0.56%	0.24%	0.01%	0.00%		1.48%
non forze lav.			0.72%	0.62%	1.42%	1.60%	4.87%	7.80%	8.55%		17.08%
TOTALE	**2.99%**	**4.21%**	**5.97%**	**7.21%**	**18.87%**	**17.51%**	**15.49%**	**14.28%**	**13.46%**	**100.00%**	**100.00%**
occupato											**32.69%**
cerca occupaz.											**3.45%**
non forze lav.											**36.68%**

Table 4. Distribution of the over 15 population in Turin (2007)

Torino (comune)	15-24 anni	25-29 anni	30-34 anni	35-44 anni	45-54 anni	55-64 anni	65-74 anni	75 anni e più	15 anni e più
1. Centro	0.38%	0.30%	0.44%	0.90%	0.72%	0.66%	0.52%	0.45%	**4.36%**
maschi	0.19%	0.15%	0.22%	0.45%	0.36%	0.33%	0.24%	0.15%	**2.09%**
femmine	0.19%	0.14%	0.22%	0.45%	0.36%	0.33%	0.28%	0.30%	**2.27%**
2. San Salvario	0.37%	0.30%	0.42%	0.83%	0.67%	0.60%	0.51%	0.52%	**4.23%**
maschi	0.19%	0.15%	0.22%	0.43%	0.33%	0.29%	0.23%	0.18%	**2.02%**
femmine	0.18%	0.15%	0.20%	0.40%	0.34%	0.32%	0.28%	0.34%	**2.21%**
3. Crocetta	0.32%	0.24%	0.35%	0.75%	0.61%	0.62%	0.54%	0.58%	**4.02%**
maschi	0.16%	0.12%	0.17%	0.37%	0.29%	0.29%	0.24%	0.19%	**1.83%**
femmine	0.16%	0.12%	0.18%	0.38%	0.32%	0.33%	0.30%	0.39%	**2.19%**
4. San Paolo	0.35%	0.25%	0.39%	0.77%	0.61%	0.54%	0.49%	0.47%	**3.87%**
maschi	0.17%	0.12%	0.20%	0.38%	0.30%	0.26%	0.22%	0.16%	**1.81%**
femmine	0.17%	0.13%	0.19%	0.39%	0.30%	0.28%	0.27%	0.31%	**2.06%**
5. Cenisia	0.40%	0.29%	0.44%	0.85%	0.71%	0.66%	0.57%	0.61%	**4.54%**
maschi	0.21%	0.15%	0.22%	0.42%	0.34%	0.32%	0.25%	0.20%	**2.11%**
femmine	0.20%	0.15%	0.22%	0.43%	0.37%	0.35%	0.32%	0.41%	**2.44%**
6. San Donato	0.51%	0.39%	0.51%	1.03%	0.86%	0.78%	0.66%	0.64%	**5.40%**
maschi	0.26%	0.20%	0.26%	0.53%	0.42%	0.37%	0.29%	0.21%	**2.55%**
femmine	0.25%	0.19%	0.25%	0.51%	0.45%	0.41%	0.36%	0.43%	**2.85%**
7. Aurora	0.45%	0.35%	0.44%	0.93%	0.69%	0.59%	0.56%	0.51%	**4.50%**
maschi	0.23%	0.18%	0.24%	0.50%	0.36%	0.29%	0.24%	0.15%	**2.19%**
femmine	0.21%	0.17%	0.21%	0.43%	0.32%	0.30%	0.32%	0.35%	**2.31%**
8. Vanchiglia	0.30%	0.23%	0.32%	0.67%	0.55%	0.52%	0.52%	0.51%	**3.63%**
maschi	0.16%	0.11%	0.16%	0.34%	0.27%	0.24%	0.23%	0.18%	**1.69%**
femmine	0.15%	0.12%	0.16%	0.33%	0.28%	0.28%	0.29%	0.32%	**1.93%**
9. Nizza Millefonti	0.31%	0.23%	0.30%	0.62%	0.50%	0.44%	0.47%	0.47%	**3.34%**
maschi	0.16%	0.11%	0.15%	0.32%	0.24%	0.21%	0.21%	0.17%	**1.57%**
femmine	0.15%	0.12%	0.15%	0.30%	0.25%	0.23%	0.26%	0.30%	**1.77%**
10. Mercati generali	0.49%	0.34%	0.47%	1.01%	0.81%	0.87%	0.87%	0.70%	**5.55%**
maschi	0.25%	0.17%	0.24%	0.50%	0.40%	0.40%	0.40%	0.27%	**2.62%**
femmine	0.24%	0.18%	0.23%	0.50%	0.42%	0.46%	0.47%	0.43%	**2.92%**
11. Santa Rita	0.54%	0.39%	0.55%	1.21%	0.96%	0.92%	1.03%	0.98%	**6.58%**
maschi	0.27%	0.19%	0.27%	0.60%	0.47%	0.42%	0.44%	0.35%	**3.02%**
femmine	0.27%	0.20%	0.28%	0.61%	0.49%	0.50%	0.58%	0.63%	**3.56%**
12. Mirafiori Nord	0.42%	0.26%	0.40%	0.86%	0.70%	0.79%	0.91%	0.66%	**5.01%**
maschi	0.22%	0.13%	0.20%	0.44%	0.34%	0.37%	0.41%	0.27%	**2.38%**
femmine	0.21%	0.13%	0.20%	0.42%	0.36%	0.43%	0.50%	0.39%	**2.64%**
13. Pozzo Strada	0.56%	0.40%	0.58%	1.19%	0.95%	0.99%	1.02%	0.83%	**6.53%**
maschi	0.29%	0.20%	0.30%	0.59%	0.46%	0.46%	0.46%	0.31%	**3.07%**
femmine	0.27%	0.21%	0.29%	0.60%	0.49%	0.53%	0.55%	0.52%	**3.46%**
14. Parella	0.49%	0.33%	0.48%	1.00%	0.84%	0.77%	0.77%	0.72%	**5.40%**
maschi	0.25%	0.16%	0.24%	0.50%	0.41%	0.37%	0.34%	0.25%	**2.51%**
femmine	0.24%	0.17%	0.24%	0.50%	0.43%	0.40%	0.43%	0.47%	**2.88%**
15. Le Vallette	0.47%	0.29%	0.36%	0.82%	0.76%	0.72%	0.72%	0.60%	**4.75%**
maschi	0.25%	0.15%	0.18%	0.42%	0.37%	0.35%	0.32%	0.23%	**2.27%**
femmine	0.23%	0.14%	0.17%	0.39%	0.38%	0.37%	0.40%	0.37%	**2.47%**
16. Madonna di Campagna	0.43%	0.32%	0.46%	0.88%	0.65%	0.61%	0.60%	0.47%	**4.41%**
maschi	0.22%	0.16%	0.23%	0.46%	0.33%	0.29%	0.27%	0.17%	**2.13%**
femmine	0.22%	0.17%	0.23%	0.41%	0.33%	0.32%	0.32%	0.30%	**2.28%**
17. Borgata Vittoria	0.44%	0.30%	0.42%	0.84%	0.67%	0.63%	0.63%	0.52%	**4.45%**
maschi	0.22%	0.15%	0.22%	0.43%	0.33%	0.30%	0.29%	0.20%	**2.14%**
femmine	0.22%	0.15%	0.20%	0.41%	0.33%	0.33%	0.35%	0.33%	**2.31%**
18. Barriera di Milano	0.58%	0.43%	0.55%	1.08%	0.80%	0.71%	0.68%	0.55%	**5.39%**
maschi	0.30%	0.22%	0.29%	0.58%	0.41%	0.35%	0.31%	0.20%	**2.67%**
femmine	0.28%	0.21%	0.25%	0.50%	0.39%	0.36%	0.37%	0.35%	**2.71%**
19. Falchera	0.28%	0.18%	0.25%	0.54%	0.40%	0.45%	0.49%	0.33%	**2.92%**
maschi	0.15%	0.09%	0.13%	0.28%	0.20%	0.20%	0.23%	0.13%	**1.41%**

femmine	0.13%	0.09%	0.12%	0.26%	0.20%	0.25%	0.25%	0.20%	**1.51%**
20. Regio Parco	0.33%	0.19%	0.24%	0.54%	0.53%	0.50%	0.48%	0.43%	**3.25%**
maschi	0.17%	0.10%	0.13%	0.27%	0.25%	0.25%	0.21%	0.16%	**1.55%**
femmine	0.15%	0.10%	0.11%	0.27%	0.28%	0.25%	0.27%	0.27%	**1.70%**
21. Madonna del Pilone	0.15%	0.09%	0.13%	0.30%	0.26%	0.25%	0.22%	0.22%	**1.61%**
maschi	0.07%	0.04%	0.06%	0.15%	0.12%	0.12%	0.10%	0.07%	**0.74%**
femmine	0.07%	0.05%	0.06%	0.15%	0.14%	0.14%	0.12%	0.14%	**0.87%**
22. Borgo Po e Cavoretto	0.20%	0.11%	0.15%	0.40%	0.36%	0.35%	0.32%	0.35%	**2.24%**
maschi	0.10%	0.05%	0.07%	0.19%	0.17%	0.17%	0.14%	0.12%	**1.02%**
femmine	0.10%	0.06%	0.08%	0.21%	0.19%	0.18%	0.18%	0.23%	**1.22%**
23. Mirafiori Sud	0.40%	0.25%	0.31%	0.71%	0.61%	0.57%	0.64%	0.52%	**4.02%**
maschi	0.21%	0.13%	0.16%	0.37%	0.30%	0.27%	0.28%	0.22%	**1.95%**
femmine	0.19%	0.12%	0.15%	0.34%	0.31%	0.29%	0.36%	0.30%	**2.07%**
TOTALE Torino	9.18%	6.49%	8.95%	18.73%	15.24%	14.56%	14.21%	12.65%	**100.00%**
maschi	4.71%	3.25%	4.55%	9.54%	7.49%	6.90%	6.36%	4.56%	**47.36%**
femmine	4.47%	3.24%	4.40%	9.19%	7.75%	7.66%	7.85%	8.09%	**52.64%**

A.2.3 Attachment 2. Questionnaire

Legend
Text of the questions to be shown or read to the interviewed
Values of the variables, or test of answers to be read or shown
Comments
Code
VARIABLE NAMES FOR CLOSED-ENDED QUESTIONS
VARIABLE NAMES FOR OPEN-ENDED QUESTIONS
Text to be ignored

List of variables without a question and which must have a value

In the questionnaire there are other variables without questions, but they are derived from observed variables

- **ID_CAMP** *Identification number of the wave. Set 1 for the current wave, 2 for the one on February 2017 and 3 for the one in June 2017.*
- **ID_INTERV** *Identification number of the interview.*
- **TIPO_INTERV** *Code for each interview:*
  - CAPI *(interview and interviewed are in the same place)*
  - CATIF *(interview through landline phone or PC)*
  - CATIC *(interview through mobile phone)*
  - CAWIC *(interview though web page form PC)*
  - CAWIS *(interview though web page from a smartphone or tablet).*
- **OPERATORE** *If = "CAWIS" o "CAWIC" set equal to* -1, *otherwise add the identification number of the interview.*
- **DATA** *Date of the interview.*
- **ORA_INIZIO** *Starting time of the interview.*
- **ORA_FINE** *Ending time of the interview.*
- **TERMINE** *Code for the end of the interview:*
  - 1: *all the six sections are filled.*
  - 2: *only sections A ,B and F are completed since the respondent did not perform any trip in the 24 hours before the interview.*
  - 3: *only section A, B and F are completed since the respondent performed only trips longer than 50 kilometres.*
  - 4: *only sections A, B and F are completed since all the trips performed by the respondent are external-external.*

- 5: *the interview was interrupted since the respondent refuses to go on If the respondent refuses to start the CAPI or CATI interview and she does not belong to the final sample, do not record the interview.*
- 6: *the interview was interrupted by technical problems.*

- **CAMPION** *It indicates if the respondent belongs to the final sample:*
  - 1: *if the respondent belongs to the final sample and TERMINE is equal to a 1, 2, 3 or 4.*
  - 2: *if the respondent lives outside the study area, therefore she does not belong to the final sample.*
  - 3: *if the respondent lives outside the study area and TERMINE is equal to a 1, 2, 3 or 4, but she does not belong to the final sample since she is an observation in excess.*
  - 4: *if the respondent lives outside the study area, but she does not belong to the final sample since TERMINE is equal to 5 or 6.*

List of the variables without questions, which must have a value (even "-1"):

- **ID_INT1XX** *Identification number of the interview reported in October 2016 by the same person*
- **ID_INT2XX** *Identification number of the interview reported in February 2017 by the same person*

Values to be assigned to all the variables (except those in the previous list) in case of missing answers

- -1: *"legitimate skip", in case of a filtered question, e.g. driving licence asked to an underage person*
- -2: *derived variable not calculated since there is no answer for the previous one*
- -6: *"no answered": if the interviewed refused to answer (CAPI or CATI) or she did not give an answer (CAWI)*
- -7: *"don not know": if the interviewed does not know the answer*
- -8: *if the related question was not posed since the survey was interrupted by the interviewed. In this case,* **TERMINE** *indicates the specific cause*
- -9: if the related *question was not posed for further causes, but the interview was not stopped.*

At the end of the questionnaire a specific field for possible notes must be provided, in order to allow encoding of the question a posteriori.

A. INTRODUCTION

If TIPO_INTERV = "CAWIC" o "CAWIS"*: show a welcome window.*

otherwise: **Good morning/evening, i am an interview belonging to** *name of the firm.* **We are administering a survey on behalf of the Politecnico di Torino. The purpose of**

this survey is to improve the mobility of travellers in the Turin metropolitan area and to understand their opinion about travel systems. Your participation is voluntary and you can withdraw at any moment. All the information that you give are reserved and anonymous (without referring to your name or phone number).

SESSO Gender: *Show the question if* TIPO_INTERV = "CAWIC" o "CAWIS"*, otherwise store the gender.*

1. Male
2. Female

ETA How old are you?

DIMORA In which municipality do you currently live? *Please indicate the specific address (street, street number, street crossing, name of a Point Of Interest) Store the municipality, and, if the location is in Turin, the zone according to the table 4 in Attachment 1; if the location is outside Italy, store the country*

Implement a window embedding Google Maps API, in order to allow the interview to specify the most precise location as possible, instead of providing the specific address. Please, follow the following examples:

- *Caffè Torino (name of a close Point fo interest)*
- *Bar NEAR Corso Principe Oddone*
- *Corso Duca degli Abruzzi CROSSING Corso Stati Uniti*
- *Via Cernaia CORNER Corso Vinzaglio*

OCCUPAZ What is your current job or employment situation?

1. Entrepreneur, freelancer
2. Officer, manager
3. Employee, trade employee
4. Worker
5. Teacher
6. Salesperson
7. Artisan, retailer
8. Student
9. Housewife
10. Retired
11. Waiting for first employment, never worked
12. Unemployed
13. **OCCUPAZ_AL** Other, specify.

If OCCUPAZ = 2, 3, 4: **CASSA_INT Are you working or do you belong cassa integrazione or in mobilità?**

1. Cassa integrazione or mobilità
2. I work

If the interviewed belongs to the final sample, then set **CAMPION** = 1 *and go on, otherwise:*

- *if* TIPO_INTERV = "CAPI" or "CATIF" *ask her to talk with another member of the household. In this case, start a new interview without storing the current one, otherwise stop the interview.*
- *if* TIPO_INTERV = "CATIC" *stop the interview, without storing the current interview*
- *if* TIPO_INTERV = "CAWIC" or "CAWIS" *set* **CAMPION** = 2 or 3 *according to the value of* DIMORA *and go on.*

B. TRAVEL DIARY

FREQ How often did you Use the following travel modes in the last month? *Possible answers: More than 3 three times a week, from 1 to 3 times a week, less than once a week, never.*

- **FREQ_BICI** Private bike
- **FREQ_BIBS** "Bike sharing" (e.g.. TOBike)
- **FREQ_MOTO** Motorbike
- **FREQ_AUCO** Private car, as driver (including rented vehicles or company cars)
- **FREQ_AUCS** "Car sharing" (e.g. enjoy, car2go, ioguido, blueTorino) as driver
- **FREQ_AUPA** Private car, as passenger
- **FREQ_TAXI** Taxi
- **FREQ_AZSB** School or company bus
- **FREQ_BUS** Urban bus, or tram
- **FREQ_METRO** Metro
- **FREQ_EXTRA** Suburban bus
- **FREQ_TRENO** Train.

n = 1

ATTIV_n We are asking some questions about where you were in the last 24 hours. Now it is *hh:mm*. **What were you doing yesterday at this time?** *In this question and in the following ones (for CATI protocol) the interview does not read all the possible answers, but she tries to infer the answer from what the interviewed says:*

1. Staying at home;
2. Working (in the usual place of work);
3. Business (working not in the usual place, e.g. in a client's office or for a meeting);

4. Working to carry loads or passengers (e.g. truck driver or delivery man);
5. Studying at school or university;
6. Medical consultations or treatment;
7. Eating and or drinking (unless the main purpose was to meet friends or relatives);
8. Grocery shopping or visiting a shopping centre;
9. Taking away or picking up people (for example, taking a child to school);
10. Other discretionary and recreational activities (all types of entertainment or sport, clubs, and voluntary work, non-vocational evening classes, political meetings).
11. Visiting friends, relatives (both at someone's home or a pub, restaurant);
12. Travelling (alone or with someone else);
13. Taking a stroll;
14. **ATTIV_AL_n** Other activities to be specified manually.

If ATTIV_n == 12 set n=n+1 and go to ***START***

If ATTIV_n <> 4 or 13 o 12 **LUOGO_n Where were you?** Please indicate the specific address (street, street number, street crossing, name of a Point Of Interest)

Use a format similar to the one of DIMORA

In this question and in the following LUOGO_n variables, enlarge the map with a square shape.

FINE_n

If ATTIV_n <> 4 o 13 **What time did you leave that place?** Specify the format (hh:mm and 0-24)

1. I have been there until now *-> Set 99:99,* **TERMINE** *= 2 got to section F*.
2. Until *hh:mm*.

If ATTIV_n == 4 or 13 **How long has this activity continued?** Specify the format (hh:mm and 0-24)

1. I have been continuing until now *-> Set 99:99 and go to section C*.
2. Until *hh:mm*. **LUOGO_n where were you, when you ended this activity?** Please indicate the specific address (street, street number, street crossing, name of a Point Of Interest) *Use a format similar to the one of DIMORA*

n = n +1

START

ATTIV_n

If ATTIV_n-1 <> 12 or 4 or 13 & n == 2

After you were:

- *"ATTIV_n-1"*".

Until:

- **"***FINE_n-1"*

Where did you go?

If ATTIV_n-1 <> 12 or 4 or 13 & n > 2

After you were:

- *"ATTIV_n-1"***".**

Until:

- **"***FINE_n-1"*

Where did you go?

If ATTIV_n-1 == 12 **Where were you going?**

If ATTIV_n-1 == 4 or 13 **Where did you go when you end this activity?** *Drop down menu with the following options (Use the following codes):*

1. At home;
2. At work (in the usual place of work);
3. At work (not in the usual place, e.g. in a client's office or for a meeting);
4. At work to carry loads or passengers (e.g. truck driver or delivery man);
5. At school or university;
6. In a hospital or medical office;
7. At bar or restaurant (unless the main purpose was to meet friends or relatives);
8. In a shop or in a shopping centre;
9. In a place to take away or to pick up people (for example, taking a child to school);
10. In a place to carry out other discretionary or recreational activities (all types of entertainment or sport, clubs, and voluntary work, non-vocational evening classes, political meetings).
11. In a place to visit friends or relatives (both at someone's home or a pub, restaurant);
12. Taking a stroll;
13. **ATTIV_AL_n** Other activities to be specified manually.

Set CONTR_N_n = 0

CONTR_N_n

If ATTIV_n-1 <> 12 or 4 or 13 e n == 2

Starting from:

- **"***ATTIV_n-1"*

At:

- “*FINE_n-1*”

To go to:

- “*ATTIV_n*”

Did you make any stops in other places to perform an activity (without considering waiting for a transport means)?

If ATTIV_n-1 <> 12 or 4 or 13 and n <> 2

Starting from when you were:

- “*ATTIV_n-1*”

At:

- “*FINE_n-1*”

To go to:

- “*ATTIV_n*”

Did you make any stops in other places to perform an activity (without considering waiting for a transport means)?

If ATTIV_n-1 == 12 or 4 or 13 & ATTIV_n <> 4 or 13

To go to:

- “*ATTIV_n*”

Did you make any stops during the journey (without considering waiting for a transport means)?

If ATTIV_n-1 == 12 or 4 o 13 & ATTIV_n == 4 or 13 **Did you make any stops during the journey (without considering waiting for a transport means)?**

1. No
2. Yes

If **CONTR_N_n** = Yes

ATTIV_n **Where did you make the first stop?** *Overwrite previously defined* **ATTIV_n**. *Drop down menu with the following options (Use the following codes):*

1. At home;
2. At work (in the usual place of work);
3. At work (not in the usual place, e.g. in a client’s office or for a meeting);
4. At work to carry loads or passengers (e.g. truck driver or delivery man);
5. At school or university;
6. In a hospital or medical office;
7. At bar or restaurant (unless the main purpose was to meet friends or relatives);
8. In a shop or in a shopping centre;
9. In a place to take away or to pick up people (for example, taking a child to school);

10. In a place to carry out other discretionary or recreational activities (all types of entertainment or sport, clubs, and voluntary work, non-vocational evening classes, political meetings).

11. In a place to visit friends or relatives (both at someone's home or a pub, restaurant);

12. Taking a stroll;

13. **ATTIV_AL_n** Other activities to be specified manually.

Set CONTR_N_n = CONTR_N_n + 1 and go back to CONTR_N_n until CONTR_N_n = No

If **CONTR_N_n** = No
LUOGO_n
If ATTIV_n <> 4 or 13
When you were:

- **"ATTIV_n"**

Where were you? Please indicate the specific address (street, street number, street crossing, name of a Point Of Interest) *Use a format similar to the one of DIMORA*
If ATTIV_n == 4 or 13 and ATTIV_n-1==12
When did you start:

- **"ATTIV_n"**

Where were you? Please indicate the specific address (street, street number, street crossing, name of a Point Of Interest) *Use a format similar to the one of DIMORA*
If ATTIV_n == 4 or 13 and n == 2
After you were:

- **"ATTIV_n-1"**

When you started:

- **"ATTIV_n"**

Did you start your travel from the same place?

If ATTIV_n == 4 or 13 and n <> 2
After you were:

- **"ATTIV_n-1"**

When you started:

- **"ATTIV_n"**

Did you start your travel from the same place?

1. Yes. *Set* **LUOGO_n == LUOGO_n-1** *and* **INIZIO_n == FINE_n-1** *and go to* **<u>END</u>**
2. No. **Where you were when you started your trip**? Please indicate the specific address (street, street number, street crossing, name of a Point Of Interest) *Use a format similar to the one of DIMORA*

If ATTIV_n-1=4 or 13 Calculate **GOO_D_n** *as the distance between LUOGO_n and LUOGO_F_n-1; If LUOGO_F_n-1 == LUOGO_n set* **GOO_D_n** *= 0.*

Otherwise If LUOGO_n-1 == LUOGO_n set **GOO_D_n** *= 0. Otherwise variables LUOGO_n-1 e LUOGO_n are used as input for Google Maps Distance Matrix API and/or Google Maps Directions API in order to obtain* **GOO_D_n** *(car distance between centroids of the two municipalities, zones or countries). Set this variable equal to 99999 if it is not possible to be estimated (too long trips or ATTIV_n-1 == 12). Google maps does not recognise some zones of Turin, therefore assign a street or a specific location inside that zone. In the following section, only trips with a value assigned to GOO_D_n (or SP_n) can be sampled.*

If ATTIV_n-1 <> 12 and ATTIV_n-1=4 or 13 set **SP_n** *= xy; where x is equal to 'I' If LUOGO_F_n-1 is within the study area, otherwise it is equal to 'E'; y is equal to 'I' If LUOGO_n is within the study area otherwise 'E'.*

Otherwise If ATTIV_n-1 <> 12 set **SP_n** *= xy; where x is equal to 'I' If LUOGO_n-1 is within the study area, otherwise it is equal to 'E'; y is equal to 'I' If LUOGO_n is within the study area otherwise 'E'.*

INIZIO_n

If ATTIV_n <> 4 or 13 **When did you reach that place**? Specify the format (hh:mm and 0-24)

If ATTIV_n == 4 or 13 **When did you begin "**ATTIV_n"? Specify the format (hh:mm and 0-24)

1. I am still travelling. *Set* **INIZIO_n** *= 99:99*
   Set **IN_CORSO_n** *= Yes*

   If n == 2 and ATTIV_n-1<>12

   Starting from when you were:

   - **"***ATTIV_n-1"*

   At:

   - **"***FINE_n-1"*

   To go to:

   - **"***ATTIV_n"*

   At:

   - **"***INIZIO_n"*

   Which travel modes you used, you are using or you are going to use? (Please list all the means following the real order and, if you used two buses, please write both of them)

   If n <> 2 and ATTIV_n-1<>12

   Starting from when you were:

   - **"***ATTIV_n-1"*

   At:

   - **"***FINE_n-1"*

   To go to:

   - **"***ATTIV_n"*

   At:

   - **"***INIZIO_n"*

Which travel modes you used, you are using or you are going to use? (Please list all the means following the real order and, if you used two buses, please write both of them)

If n == 2 and ATTIV_n-1==12

To go to:

- **"***ATTIV_n***"**

At:

- **"***INIZIO_n***"**

Which travel modes you used, you are using or you are going to use? (Please list all the means following the real order and, if you used two buses, please write both of them)

MEZZO_n_1 First mode: *Drop down menu to select one of the following choices:*

1. **PIEDI** Walking, wheelchair, roller skate (for at least 5 minutes)
2. **BICI** Bike
3. **BIBS** "Bike sharing" (e.g. TOBike)
4. **MOTO** Motorbike
5. **AUCO** Private car, as driver (including rented vehicles or company cars)
6. **AUCS** "Car sharing" (e.g. enjoy, car2go, ioguido, blueTorino) as driver
7. **AUPA** Private car, as passenger
8. **TAXI** Taxi
9. **AZSB** School or company bus
10. **BUS** Urban us or tram
11. **METRO** Metro
12. **EXTRA** Suburban bus
13. **TRENO** Train
14. **AEREO** Airplane
15. **NAVE** Ship.

- **MEZZO_n_2 Second mode:** *Drop down with "None" as a default value and the same options in the previous question.*
- *If MEZZO_n_2 <> "None" add the "Third mode"; the corresponding variable* **MEZZO_n_3** *has the same previous drop down menu. Repeat the question until the respondent adds new travel modes.*

INIZIO_n What time are you going to arrive "*ATTIV_n***"?** At *hh:mm*. (*Overwrite* **INIZIO_n***).*

Go to section C

2. At *hh:mm*

Set **IN_CORSO_n** *= No*

If n == 2 and ATTIV_n-1<>12

Starting from where you were:

- **"***ATTIV_n-1***"**

At:

- *“FINE_n-1”*

To go to:

- *“ATTIV_n”*

At:

- *“INIZIO_n”*

Which travel modes you used, you are using or you are going to use? (Please list all the means following the real order and, if you used two buses, please write both of them)

If n <> 2 and ATTIV_n-1<>12

Starting from where you were:

- *“ATTIV_n-1”*

At:

- *“FINE_n-1”*

To go to:

- *“ATTIV_n”*

At:

- *“INIZIO_n”*

Which travel modes you used, you are using or you are going to use? (Please list all the means following the real order and, if you used two buses, please write both of them)

If n == 2 and ATTIV_n-1==12

To go to:

- *“ATTIV_n”*

At:

- *“INIZIO_n”*

Which travel modes you used, you are using or you are going to use? (Please list all the means following the real order and, if you used two buses, please write both of them)

- **MEZZO_n_1** **First mode:** *Drop down menu to select one of the following choices:*
  1. PIEDI Walking, wheelchair, roller skate (for at least 5 minutes)
  2. BICI Bike
  3. BIBS “Bike sharing” (e.g. TOBike)
  4. MOTO Motorbike
  5. AUCO Private car, as driver (including rented vehicles or company cars)
  6. AUCS “Car sharing” (e.g. enjoy, car2go, ioguido, blueTorino) as driver
  7. AUPA Private car, as passenger

8. **TAXI** Taxi
9. **AZSB** School or company bus
10. **BUS** Urban bus or tram
11. **METRO** Metro
12. **EXTRA** Suburban bus
13. **TRENO** Train
14. **AEREO** Airplane
15. **NAVE** Ship.

- **MEZZO_n_2 Second mode:** *Drop down with "None" as a default value and the same options in the previous question.*
- *If MEZZO_n_2 <> "None" add the "Third mode"; the corresponding variable* **MEZZO_n_3** *has the same previous drop down menu. Repeat the question until the respondent adds new travel modes.*

END

FINE_n

If ATTIV_n <> 4 or 13

After you were:

- **"***ATTIV_n"*

What time did you leave that place? Specify the format (hh:mm and 0-24)

1. I have been there until now. *Set* **FINE_n** = 99:99 *and go to section C*
2. At *hh:mm*

If ATTIV_n == 4 or 13 **When did you end the activity that you were carrying out?** Specify the format (hh:mm and 0-24)

1. It is still occurring. *Set* **FINE_n** = 99:99 *and go to section C*
2. At *hh:mm*

LUOGO_F_n *If* ATTIV_n == 4 or 13 **When you ended that activity, where you in the same place from where you started?**

1. Yes. *Set* **LUOGO_F_n** = 0
2. No. **LUOGO_F_n Where were you?** Please indicate the specific address (street, street number, street crossing, name of a Point Of Interest*) Use a format similar to the one of DIMORA*

Set **n = n+1** *and go back to* ***START***

C. FOCUS ON A MACRO-TRIP

The software samples one of the trips reported in the previous section, including the one that is occurring, and it generates the macro-trip using the following procedure:

1) *If at least one of the recorded trips has GOO_D_n <= 50 km, then all the trips GOO_D_n > 50 km has a null sampling probability; trips with GOO_D_n=0 are not considered.*
If all the trips have GOO_D_n > 50 km set **TERMINE** *= 3 and go to section F.*

2) *LUOGO_n: If at least one of the recorded trips has both origin and destination within the study area, then all the other trips have a null sampling probability;*
otherwise If at least one of the recorded trips has either the origin or the destination within the study area, then all the trips with both origin and destination outside the study area have a null sampling probability;
otherwise set **TERMINE** *= 4 and go to section F.*

3) *Sample one of the trip among those not excluded and generate the variable* **ESTRAZ** *which is equal to 1 If both the origin and the destination are within the study area, otherwise it is equal to 2.*

4) *Creation of the macro-trip considering INIZIO_n and FINE_n: If all the three following conditions are satisfied: (1) the duration of the activity either at the origin or at the destination is less than 30 minutes, (2) there are one or two trips neighbouring to the origin and/or the destination, and (3) they do not have a null sampling probability, then define a macro-trip as the union of the two or three contiguous trips, otherwise the macro-trip corresponds to the sampled trip. Repeat the process of aggregation until one of the previous three conditions is not satisfied.*

5) *Create the variables* **ATTIV_O, ATTIV_D, LUOGO_O, LUOGO_D, FINE_O, INIZIO_D***, considering the origin of the first trip in the macro-trip and the destination of the last trip in the macro-trip. If* **ATTIV_O** *= 4 or 13, in order to assign* **LUOGO_O** *do not use* **LUOGO_n***, but* **LUOGO_F_n-1.** *Create the variables* **SOSTA_1, SOSTA_2,…SOSTA_s***, to store the activities performed between* **ATTIV_O** and **ATTIV_D.**

6) *Create the variables* **DURATA** *which is equal to INIZIO_D - FINE_O and* **TEMPOTOT** *which is equal to DURATA minus the durations of activities lasting less than 30 minutes within the macro-trip.*

7) *Create variable* **IN_CORSO_S** *which is equal to Yes If the last trip of the macro-trip is still occurring.*

8) *Create 15 binary variables* **PIEDI_S, …, NAVE_S** *which are equal to "Yes" If the corresponding travel mode was used in at least one trip in the macro-trip.*

9) *Create the following four variables:* **MULT_S** *which is equal to "Yes" If more than one of the previous 15 binary variables is equal to "Yes";* **TP_S** *which is equal to "Yes" if at least one of the following variables is equal to "Yes": AZSB_S, BUS_S, METRO_S, EXTRA_S or TRENO_S, and* **MECC_S** *which is equal to "Yes" if one of the variable "_S" besides "PIEDI_S" is equal to "Yes";* **MOTOR_S** *which is equal to "Yes" if at least one of the variables generated at step 8) is equal to "Yes", excluding BICI_S, BIBS_S and PIEDI_S.*

If IN_CORSO_S = Yes: **Please, focus on the trip that you are carrying out starting from:**

- "*ATTIV_O*", **in** "*LUOGO_O*"

At:

- "*FINE_O*"

To go to:

- "*ATTIV_D*", **in** "*LUOGO_D*", **where you are going to arrive**

If variables SOSTA_1, SOSTA_2 … exist: **with stop** "*SOSTA_1*", "*SOSTA_2*", "*SOSTA_...*".

To perform this trip you used or you are using the following travel modes:

- *List all the travel means for which the corresponding variable "_S" is equal to "Yes" using a bulleted list.*

otherwise: **Please, focus on the trip that you carried out starting from:**

- "*ATTIV_O*", **in** "*LUOGO_O*"

At:

- "*FINE_O*"

To go to:

- "*ATTIV_D*", **in** "*LUOGO_D*"

Where you arrived at:

- "*INIZIO_D*"

If variables SOSTA_1, SOSTA_2 … exist: **with stop** "*SOSTA_1*", "*SOSTA_2*", "*SOSTA_...*".

To perform this trip you used or you are using the following travel modes:

- *List all the travel means for which the corresponding variable "_S" is equal to "Yes" using a bulleted list.*

PREVAL *If MULT_S = "Yes":* **Among all the travel modes that you used for this trip, in which one did you spend most of the time, excluding walking trips?** *Drop down menu with only the travel modes used in the macro-trip, excluding walking. Variable with the same format of variables MEZZO_n_x.*

Otherwise set PREVAL equal to the only used mode.

If PREVAL = BICI set **MODO** *= BIKE, If PREVAL = BIBS set* **MODO** *= BSHAR, If PREVAL = AUCO or PREVAL = AUPA or PREVAL = MOTO set* **MODO** *= CAR, If PREVAL = AUCS set* **MODO** *= CSHAR, If PREVAL = AZSB or PREVAL = BUS or PREVAL = METRO or PREVAL = EXTRA or PREVAL = TRENO set* **MODO** *= TP, If PREVAL = TAXI set* **MODO** *= TAXI, If PREVAL = PIEDI set* **MODO** *= PIEDI.*

The two previous variables are used as input to Google Maps Distance Matrix API e Google Maps Directions API in order to obtain the following 5 variables: **GOO_TAU** *(estimated car travel time),* **GOO_TTP** *(estimated travel time on public transport),* **GOO_TPI** *(estimated walking travel time),* **GOO_DAU** *(estimated car distance),* **GOO_DPI** *(estimated walking distance). These variables are equal to -1 if the corresponding mode is not available (e.g. airplane, short trips).*

FREQ_SPOST **How often do you perform this trip?** *Possible answers: More than 3 three times a week, from 1 to 3 times a week, less than once a week, never.*

If IN_CORSO_S = Yes: change the verb of the following four questions to a present form:

PERSONE *If TP_S = No:* **How many people travelled with you at least for a part of the trip?**

otherwise: **How many people travelled with you for at least a part of the trip, without considering other passengers on the public transport means?** *Specify a number*

INGOMBRI **During your trip, did you carry any heavy goods or bulk (bags, package, luggage, …)?**

1. Yes

2. No

BAMBINI *If PERSONE>0:* **Were there a child aged 3 or less, or did you have to push a wheelchair?**

1. Yes
2. No

ANIMALI **Were there an animal with you?**

1. Yes
2. No

ATT_SPOST **Which of the following activities did you perform during this trip?** *Multiple answer question. Possible answers: Yes or No.*

- **M_STUD** Studying or working
- **M_MUS** Listening to music or radio
- **M_VID** Watching a video or a film
- **M_INT** Surfing the internet
- **M_TEL** Phoning
- **M_SMS** Reading or writing messages or e-mails
- **M_LETT** Reading a book or a paper or electronic document
- **M_PARL** Talking with other travellers
- **M_GIOC** Playing alone or together with someone else
- **M_PENS** Thinking
- **M_GUARD** Watching the landscape, shop windows or people
- **M_MANG** Eating, drinking, smoking
- **M_DORM** Sleeping or resting.

If MECC_S = Yes and IN_CORSO_S = Yes: **MARCIA** **All the trips that you performed from "***FINE_O***" to "***INIZIO_D***" last** *TEMPOTOT* **minutes.**

How long did you walk or are you going to walk to reach the vehicle(s) you used and to reach your final destination? *Specify a number lower than di TEMPOTOT, in minutes.*

If MECC_S = Yes and IN_CORSO_S = No: **MARCIA** **All the trips that you performed from "***FINE_O***" to "***INIZIO_D***" last** *TEMPOTOT* **minutes.**

How long did you walk to reach the vehicle(s) you used and to reach your final destination? *Specify a number lower than di TEMPOTOT, in minutes.*

otherwise set TEMPOTOT = MARCIA.

If TP_S = Yes: **ATTESTP** **How long did you wait at the transit stop(s) the public transport means that you used?** *Specify a number lower than TEMPOTOT – MARCIA, in minutes.*

otherwise set ATTESTP = 0.

If AUPA_S = Yes or TAXI_S = Yes: **ATTESAU How long did you wait on the street to be picked up for this trip?** *Specify a number lower than TEMPOTOT – MARCIA, in minutes. Do not consider the waiting time at home, in a bar, …*
otherwise set ATTESAU = 0.

If BIBS_S = Yes set **BIBS_ABBON** *= Yes and:* **BIBS_TEMPO Among all the adopted travel modes to go from:**

- *"ATTIV_O"*

To:

- *"ATTIV_D"*

You reported bike sharing. How long have you been using that service? *Possible answers: from less than one month, from one to six months, from six months to one year, from one to two years, from more than two years.*

If BIBS_S = Yes: **BIBS_PASS Which travel mode did you use instead of bike sharing to carry out trips like this one?** *Multiple answer question. Possible answers: Yes or No*

- **BIBS_PIEDI** Walking, wheelchair, roller skate (for at least 5 minutes)
- **BIBS_BICI** Bike
- **BIBS_MOTO** Motorbike
- **BIBS_AUCO** Private car, as driver (including rented vehicles or company cars)
- **BIBS_AUCS** "Car sharing" (e.g. enjoy, car2go, ioguido, blueTorino) as driver
- **BIBS_AUPA** Private car, as passenger
- **BIBS_TAXI** Taxi
- **BIBS_AZSB** School or company bus
- **BIBS_BUS** Urban bus or tram
- **BIBS_METRO** Metro
- **BIBS_EXTRA** Suburban bus
- **BIBS_TRENO**Train

If MOTO_S = Yes or AUCO_S = Yes go on, otherwise go to ***AUCS****:*
COND_DIST *If MULT_S= Yes* **To go from:**

- *"ATTIV_O"*

To:

- *"ATTIV_D"*

You reported motorbike as a travel means to perform at least a part of this trip. Among GOO_DAU kilometres that you took, how many kilometres did you cover using this mode? *In kilometres.*

otherwise: **To go from:**

- *"ATTIV_O"*

To:

- *"ATTIV_D"*

You reported motorbike as a travel means to perform at least a part of this trip. How many kilometres did you cover using this mode? *In kilometres.*

If AUCO_S = Yes **COND_ALIM** **Which is the fuel type of this vehicle?**

1. Petrol
2. Diesel
3. LPG
4. Methane gas
5. Electric power
6. Hybrid vehicle
7. I do not know

Calculate **COND_CARB**, *i.e. the cost of fuel, considering MOTO_S, AUCO_S, COND_DIST, COND_ALIM. If COND_ALIM = Petrol set* **COND_CARB** *= COND_DIST*0.098 €/km, If COND_ALIM = Diesel set* **COND_CARB** *= COND_DIST*0.060 €/km, If COND_ALIM = LPG set* **COND_CARB** *= COND_DIST*0.079 €/km, If COND_ALIM = Methane gas set* **COND_CARB** *= COND_DIST*0.043 €/km, If COND_ALIM = Electric power set* **COND_CARB** *= COND_DIST*0.032 €/km, If COND_ALIM = Hybrid vehicle set* **COND_CARB** *= COND_DIST*0.086 €/km, COND_ALIM = I do not know set* **COND_CARB** *= COND_DIST*0.081 €/km.*

If MOTO_S = Yes and AUCO_S = No, set **COND_CARB** *= COND_DIST*0.035 €/km*

If AUCO_S = Yes and PERSONE>0 **COND_PASS** **Whom did you travel with?** *Multiple answers.*

1. Partner, relative
2. Friend
3. Colleague
4. A person who requested a car pooling (e.g. Easymoove, Bringme, BlaBlaCar, Zego)
5. Oher

COND_PARK_O **Where was this vehicle parked, before using it for this trip?**

1. Free on-street park
2. Paying on-street park
3. Free public dedicated parking space
4. Paying public dedicated parking space

5. Residential park or garage
6. Private park or garage

COND_PARK_D Where dis you park or are you going to park the vehicle at the end of this trip?

1. Free on-street park
2. Paying on-street park
3. Free public dedicated parking space
4. Paying public dedicated parking space
5. Residential park or garage
6. Private park or garage

COND_PARK_COST *If ((COND_PARK_O=2 or 4) or (COND_PARK_D=2 or 4)):*
If IN_CORSO_S = Yes: **Which is the park cost, before, during and at the end this trip? Please do not consider the cost of renting a garage, parking slot or subscriptions.** *In euros.*
otherwise: **Which is the park cost, before, during and at the end this trip? Please do not consider the cost of renting a garage, parking slot or subscriptions.** *In euros.*
COND_PED *If IN_CORSO_S = Yes:* **If you travelled or you are travelling on a highway, how much was the toll?** *In euros; if empty answer, set 0.*
otherwise: **If you travelled on a highway, how much was the toll?** *In euros; if empty answer, set 0.*
Calculate **COND_COST** *summing up COND_CARB, COND_PARK_COST and COND_PED.*
COND_PAGA Who bore the trip costs (fuel, parking costs, tolls)?

1. Me
2. Me, the driver and other passengers
3. Not me.

AUCS
If AUCS_S = Yes set **AUCS_ABBON** *= Yes and go on, otherwise go to* ***TP****:*

AUCS_COMP To go from:

- *"ATTIV_O"*

To:

- *"ATTIV_D"*

You reported car sharing as travel mode to perform at least a part of the trip. Which was the operator?

1. IoGuido
2. Enjoy
3. Car2Go

4. BlueTorino
5. Other

AUCS_COST How much did you pay for this trip? Please do not consider subscription costs. *In euros.*

AUCS_PAGA Who bore the trip costs (fuel, parking costs, tolls)?

1. Me
2. Me, the driver and other passengers
3. Not me.

AUCS_TEMPO How long have you been a car sharing member? *Possible answers: from less than one month, from one to six months, from six months to one year, from one to two years, from more than two years.*

AUCS_PASS Which travel mode did you use instead of car sharing to carry out trips like this one? *Multiple answer question. Possible answers: Yes or No*

- **AUCS_PIEDI** Walking, wheelchair, roller skate (for at least 5 minutes)
- **AUCS_BICI** Bike
- **AUCS_MOTO** Motorbike
- **AUCS_AUCO** Private car, as driver (including rented vehicles or company cars)
- **AUCS_AUCS** "Car sharing" (e.g. enjoy, car2go, ioguido, blueTorino) as driver
- **AUCS_AUPA** Private car, as passenger
- **AUCS_TAXI** Taxi
- **AUCS_AZSB** School or company bus
- **AUCS_BUS** Urban bus or tram
- **AUCS_METRO** Metro
- **AUCS_EXTRA** Suburban bus
- **AUCS_TRENO**Train

TP
If TP_S = Yes go on, otherwise go to ***AUPA****:*

If IN_CORSO_S = Yes: **TP_SEDUTO To go from:**

- *"ATTIV_O"*

To:

- *"ATTIV_D"*

You reported public transport as travel means to perform at least a part of the trip. Are you seated or stood up during the trip? *Possible answers: seated, stoop up or both of them.*

otherwise: **To go from:**

- *"ATTIV_O"*

To:

- *"ATTIV_D"*

You reported public transport as travel means to perform at least a part of the trip. Were you seated or stood up during the trip? *Possible answers: seated, stoop up or both of them.*

TP_TITOL *If IN_CORSO_S = Yes:* **Which type of ticket are you using for this trip? If you are using more than one ticket, please write all of them (e.g. ticket for a line and subscription for another line)** *Multiple answer question.*

otherwise: **Which type of ticket did you use for this trip? If you are using more than one ticket, please write all of them (e.g. ticket for a line and subscription for another line)** *Multiple answer question.*

1. No ticket
2. Single ticket
3. Multiple tickets
4. Weekly subscription
5. Monthly subscription
6. Annual subscription

COSTO_BIGL *If TP_TITOL = 2:* **How much did you pay for the ticket(s) that you used?** *In euros.*

otherwise set **COSTO_BIGL** *= 0.*

If TP_BIGL = 3:

COST_CARN **How much did you pay for the multiple ticket(s) that you used?** *In euros.*

NUM_CARN **How many trips are you allowed to perform with your multiple tickets?**

otherwise set **COST_CARN** *= 0.*

COSTO_ABBON *If TP_TITOL = 4, 5 or 6:* **How much did you pay for the subscription that you used?** *In euros.*

If TP_TITOL = 4 **COSTO_ABBON_S** *= COSTO_ABBON/14*

If TP_TITOL = 5 **COSTO_ABBON_M** *= COSTO_ABBON/60*

If TP_TITOL = 6 **COSTO_ABBON_A** *= COSTO_ABBON/730*

otherwise set **COSTO_ABBON_S** *= COSTO_ABBON_M = COSTO_ABBON_A = 0.*

Calculate the total cost **TP_COST** *considering COSTO_BIGL and COSTO_ABBON, supposing an usage frequency in case of subscription:* **TP_COST** *= COSTO_BIGL + COST_CARN/NUM_CARN + COSTO_ABBON_S + COSTO_ABBON_M + COSTO_ABBON_A.*

AUPA

If AUPA_S = Yes go on, otherwise go to ***TAXI****:*

AUPA_GUID **To go from:**

- *"ATTIV_O"*

To:

- *“ATTIV_D”*

You reported using car as a passenger for at least a part of the trip. Who drove the car?

1. Partner, relative
2. Friend
3. Colleague
4. Car pooler (e.g. Easymoove, Bringme, BlaBlaCar, Zego)
5. Other

AUPA_DIST *If MULT_S= Yes* **Among GOO_DAU kilometres travelled, how many kilometres did you cover on this mode?** *In kilometres.*
otherwise: **How many kilometres did you cover on this mode?** *In kilometres.*
AUPA_ALIM Which is the fuel type of this vehicle?

1. Petrol
2. Diesel
3. LPG
4. Methane gas
5. Electric power
6. Hybrid vehicle
7. I do not know

Calculate **AUPA_CARB**, *i.e. the cost of fuel, considering MOTO_S, AUCO_S, AUPA_DIST, AUPA_ALIM. If AUPA_ALIM = Petrol set* **AUPA_CARB** *= AUPA_DIST*0.098 €/km, If AUPA_ALIM = Diesel set* **AUPA_CARB** *= AUPA_DIST*0.060 €/km, If AUPA_ALIM = LPG set* **AUPA_CARB** *= AUPA_DIST*0.079 €/km, If AUPA_ALIM = Methane gas set* **AUPA_CARB** *= AUPA_DIST*0.043 €/km, If AUPA_ALIM = Electric power set* **AUPA_CARB** *= AUPA_DIST*0.032 €/km, If AUPA_ALIM = Hybrid vehicle set* **AUPA_CARB** *= AUPA_DIST*0.086 €/km, AUPA_ALIM = I do not know set* **AUPA_CARB** *= AUPA_DIST*0.081 €/km.*
AUPA_PARK_O Where was this vehicle parked, before using it for this trip?

1. Free on-street park
2. Paying on-street park
3. Free public dedicated parking space
4. Paying public dedicated parking space
5. Residential park or garage
6. Private park or garage
7. I do not know

AUPA_PARK_D Where dis you park or are you going to park the vehicle at the end of this trip?

1. Free on-street park
2. Paying on-street park
3. Free public dedicated parking space
4. Paying public dedicated parking space
5. Residential park or garage
6. Private park or garage
7. I do not know

AUPA_PARK_COST *If ((AUPA_PARK_O=2 or 4) or (AUPA_PARK_D=2 or 4)):*
If IN_CORSO_S = Yes: **Which is the park cost, before, during and at the end this trip? Please do not consider the cost of renting a garage, parking slot or subscriptions.** *In euros.*
otherwise: **Which is the park cost, before, during and at the end this trip? Please do not consider the cost of renting a garage, parking slot or subscriptions.** *In euros.*
AUPA_PED *If IN_CORSO_S = Yes: :* **If you travelled or you are travelling on a highway, how much was the toll?** *In euros; if empty answer, set 0.*
otherwise: **If you travelled on a highway, how much was the toll?** *In euros; if empty answer, set 0.*
Calculate **AUPA_COST** *summing up AUPA_CARB, AUPA_PARK_COST and AUPA_PED.*
AUPA_PAGA Who bore the trip costs (fuel, parking costs, tolls)?

1. Me
2. Me, the driver and other passengers
3. Not me.

TAXI
If TAXI_S = Yes go on, otherwise go to section D:

TAXI_PREN To go from:

- *"ATTIV_O"*

To:

- *"ATTIV_D"*

You reported taxi to perform at least a part of this trip. How did you book it?

1. By phone or online
2. I went to a taxi park
3. I stopped it on the way
4. Other

TAXI_COST How much did you pay for this trip? *In euros.*
TAXI_PAGA Who bore the cost?

1. Me
2. Me and other passengers
3. Not me.

D. ATTITUDINAL SURVEY

To sum up, in order to travel from:

- *“ATTIV_O”*

To:

- *“ATTIV_D”*

You used the following travel modes:

- *List of the travel modes with the corresponding variable “_S” is equal to “Yes” using a bulleted list.*

If FREQ_SPOST <> Never (besides this time) **PASS_MODO Please, list all the travel means that you used to perform this trip in the past.** *Multiple answer question. Possible answers: Yes or No.*

- **PASS_PIEDI** Walking, wheelchair, roller skate (for at least 5 minutes)
- **PASS_BICI** Bike
- **PASS_BIBS** “Bike sharing” (e.g.. TOBike)
- **PASS_MOTO** Motorbike
- **PASS_AUCO** Private car, as driver (including rented vehicles or company cars)
- **PASS_AUCS** “Car sharing” (e.g. enjoy, car2go, ioguido, blueTorino) as driver
- **PASS_AUPA** Private car, as passenger
- **PASS_TAXI** Taxi
- **PASS_AZSB** School or company bus
- **PASS_BUS** Urban bus or tram
- **PASS_METRO** Metro
- **PASS_EXTRA** Suburban bus
- **PASS_TRENO** Train
- **PASS_AEREO** Airplane
- **PASS_NAVE** Ship.
- **PASS_ALTRO** Other.

FUT_MODO Please, list all the travel means that you might use to perform this trip in the future. *Multiple answer question. Possible answers: Yes or No.*

- **FUT_PIEDI** Walking, wheelchair, roller skate (for at least 5 minutes)
- **FUT_BICI** Bike
- **FUT_BIBS** "Bike sharing" (e.g. TOBike)
- **FUT_MOTO** Motorbike
- **FUT_AUCO** Private car, as driver (including rented vehicles or company cars)
- **FUT_AUCS** "Car sharing" (e.g. enjoy, car2go, ioguido, blueTorino) as driver
- **FUT_AUPA** Private car, as passenger
- **FUT_TAXI** Taxi
- **FUT_AZSB** School or company bus
- **FUT_BUS** Urban bus or tram
- **FUT_METRO** Metro
- **FUT_EXTRA** Suburban bus
- **FUT_TRENO** Train
- **FUT_AEREO** Airplane
- **FUT_NAVE** Ship.
- **FUT_ALTRO** Other.

If IN_CORSO_S = Yes change the verb of the following question in a present form:
IMPR **Were there any particular events or accidents during the trip? Please, list all of them:** *Multiple answer question. Possible answers: Yes or No.*

If AZSB_S = Yes or BUS_S = Yes or METRO_S = Yes or EXTRA_S = Yes or TRENO_S = Yes:

- **IMPR_STOP** Stopped vehicle between two transit stops
- **IMPR_RIT** Unusual delay of public transport
- **IMPR_TP** I missed the bus, tram or train and, therefore, my delay was greater than 15 minutes

The following variables must be always shown **IMPR_AGGR** Pickpocketing or aggressive passengers

- **IMPR_PANNE** Broken down vehicle
- **IMPR_CONG** Stopped vehicle because of traffic congestion
- **IMPR_AUTO** Dangerous travel behaviour of a driver or motorbiker
- **IMPR_AUPE** Dangerous travel behaviour of a biker or pedestrian
- **IMPR_INCID** Vehicle accident

- IMPR_ALTRO Other.

Could you please give your opinion about the overall trip, by using the following evaluation scales?

COGNIT_1

1. This travel was low standard
2. This travel was scarce standard
3. This travel was normal standard
4. This travel was decent standard
5. This travel was high standard.

COGNIT_2

1. This travel was worst I can think of
2. This travel was a little bit worst I can think of
3. This travel was as I can think of
4. This travel was a little bit best I can think of
5. This travel was best I can think of

COGNIT_3

1. This travel worked poorly
2. This travel worked quite poorly
3. This travel worked as usual
4. This travel worked quite well
5. This travel worked well

SODDISF **Overall, how do you consider your satisfaction level of this trip?**

1. I am very dissatisfied
2. I am quite dissatisfied
3. I am neither satisfied nor dissatisfied
4. I am quite satisfied
5. I am very satisfied

GRADIM **Overall, did you enjoy this trip?**

1. No, at all
2. No, not much
3. So and so
4. Yes, quite

5. Yes, very much

During this trip, did you feel…?

AFFECT_1

1. Very worried I would not be in time
2. Quite worried I would not be in time
3. Indifferent to be in time
4. Quite confident I would be in time
5. Very confident I would be in time

AFFECT_2

1. Very time pressed
2. Quite time pressed
3. Indifferent
4. Quite relaxed
5. Very relaxed.

AFFECT_3

1. Very stressed
2. Quite stressed
3. Indifferent
4. Quite calm
5. Very calm.

AFFECT_4

1. Very tired
2. Quite tired
3. Indifferent
4. Quite alert
5. Very alert.

AFFECT_5

1. Very bored
2. Quite bored
3. Indifferent
4. Quite enthusiastic
5. Very enthusiastic.

AFFECT_6

1. Very fed up

2. Quite fed up
3. Indifferent
4. Quite engaged
5. Very engaged.

E. STATED-PREFERENCES EXPERIMENTS

1) *Calculate:*
   - *The total cost of the macro-trip:* **COSTO** *= COND_COST + AUCS_COST + AUPA_COST + TAXI_COST + TP_COST*
   - *The total waiting time:* **ATTESA** *= ATTESTP + ATTESAU*
   - *If* **MODO** *<> PIEDI, the in-vehicle travel time:* **TEMPO** *= TEMPOTOT – (ATTESA + MARCIA), otherwise If* **MODO** *= PIEDI TEMPO = MARCIA*
2) *Generate a Stated-preferences experiment with one alternative, namely "switch", and the base option "opt-out", which corresponds to using the already adopted travel mode. The final question is a labelled experiment, where the label is the attribute "travel mode", which can be equal to the following six levels (obtained by aggregating the travel means into the six classes reported in the PREVAL question): private car, car sharing, taxi (individual or not), public transport, bike and bike sharing. In the following, the six classes are respectively labelled as: CAR, CSHAR, TAXI, TP, BICI, BSHAR. All the alternatives have four quantitative attributes: trip cost, in-vehicle time, waiting time and walking time. These attributes are equal to COSTO, TEMPO, ATTESA and MARCIA for the opt-out alternative, whereas they can be equal to values with 3 levels (low, base and high) for the "switch" alternative. All the levels are reported in* ***Attachment 4***.
3) *An orthogonal fractional factorial design with 18 different questions divided into 3 blocks is generated, thereby each interviewed has to face with 6 choice experiments, one for each travel mode. The fractional design is described in* ***Attachment 5***. *Unless the macro-trip was performed on foot, in one of these experiments the travel mode for the "switch" alternative is equal to that of "opt-out" alternative (MODO).*
4) *According to the factorial design and the specific block of questions assigned to the interviewed (BLOCK), calculate the values of the following 18 variables (which are the attributes of the "switch" alternative in the 6 choice tasks, see* ***Attachment 3***): **COSTO_SW_CAR**, **TEMPO_SW_CAR**, **MARCIA_SW_CAR**, **COSTO_SW_CSHAR**, **TEMPO_SW_CSHAR**, **MARCIA_SW_CSHAR**, **COSTO_SW_TAXI**, **TEMPO_SW_TAXI**, **ATTESA_SW_TAXI**, **MARCIA_SW_TAXI**, **COSTO_SW_TP**, **TEMPO_SW_TP**, **ATTESA_SW_TP**, **MARCIA_SW_TP**, **TEMPO_SW_BICI**, **MARCIA_SW_BICI**, **TEMPO_SW_BSHAR**, **MARCIA_SW_BSHAR**.

Please, focus on the trip or trips that you carried out from *"FINE_O"* **until** *"INIZIO_D"* **after you have been** *"ATTIV_O"* **to reach** *"ATTIV_D"*.

If MECC_S = Yes go on, otherwise go to ***PIEDI***.

Considering your previous answers, your trips should have the following characteristics:

- **In-vehicle travel time, excluding possible intermediate stops:** *TEMPO* **minutes**
- **Waiting time:** *ATTESA* **minutes**
- **Walking time:** *MARCIA* **minutes**
- **Total cost (fuel, tolls, parking costs, tickets):** *COSTO* **euros (based on your answers).**

You used *MODO (underscored)* **to travel for most of the time, besides:**
list the other travel means.

Generate the **BLOCK** *variable, which is equal to 1, 2 or 3; assign values to the following variables according to tables in Attachment 3.*

SWITCH_CAR Please imagine that you have an available car that you can drive.

If you had to perform the same trip again in the future, what would be your propensity to use the following mode with travel characteristics explained below, instead of the mode or modes that you currently adopt? *Answer with five levels: "I am not at all inclined to use the switching mode", "I am not very inclined to use the switching mode", "Neutral", "I am slightly inclined to use the switching mode", "I am strongly inclined to use the switching mode".*

- **In-vehicle travel time:** *If TEMPO_SW_CAR = 0* **"less than one minute"**, *otherwise TEMPO_SW_CAR* **minutes**
- **Walking time from/to the parking place:** *MARCIA_SW_CAR* **minutes**
- **Fuel and parking cost:** *COSTO_SW_CAR* **euros.**

In the below box the characteristics of your trip performed on *MODO (underscored)* **are recalled:**

- **In-vehicle travel time, excluding possible intermediate stops:** *TEMPO* **minutes**
- **Waiting time:** *ATTESA* **minutes**
- **Walking time:** *MARCIA* **minutes**
- **Total cost (fuel, tolls, parking costs, tickets):** *COSTO* **euros (based on your answers).**

SWITCH_CSHAR Independently on what you reported in the previous question, please imagine that you are a member of a car sharing service which is suitable for your trip and you can use it. *If needed, read or show a description of car sharing.*

If you had to perform the same trip again in the future, what would be your propensity to use the following mode with travel characteristics explained below, instead of the mode or modes that you currently adopt? *Answer with five levels: "I am not at all inclined to use the switching mode", "I am not very inclined to use the switching mode", "Neutral", "I am slightly inclined to use the switching mode", "I am strongly inclined to use the switching mode".*

- **In-vehicle travel time:** *If TEMPO_SW_CSHAR = 0* **"less than one minute"**, *otherwise TEMPO_SW_CSHAR* **minutes**
- **Walking time from/to the parking place:** *MARCIA_SW_CSHAR* **minutes**

- **Total costs:** *COSTO_SW_CSHAR* **euros.**

In the below box the characteristics of your trip performed on *MODO (underscored)* **are recalled:**

- **In-vehicle travel time, excluding possible intermediate stops:** *TEMPO* **minutes**
- **Waiting time:** *ATTESA* **minutes**
- **Walking time:** *MARCIA* **minutes**
- **Total cost (fuel, tolls, parking costs, tickets):** *COSTO* **euros (based on your answers).**

SWITCH_TP Independently on what you reported in the previous question, please imagine that there is a <u>new public transport line</u> that you can use to perform the same trip without any transfers.

If you had to perform the same trip again in the future, what would be your propensity to use this new line with travel characteristics explained below, instead of the mode or modes that you currently adopt? *Answer with five levels: "I am not at all inclined to use the switching mode", "I am not very inclined to use the switching mode", "Neutral", "I am slightly inclined to use the switching mode", "I am strongly inclined to use the switching mode".*

- **in-vehicle travel time:** *If TEMPO_SW_TP = 0* **"less than one minute"**, *otherwise TEMPO_SW_TP* **minutes**
- **Waiting time at the transit stop(s):** *ATTESA_SW_TP* **minutes**
- **walking time:** *MARCIA_SW_TP* **minutes**
- **Ticket cost:** *COSTO_SW_TP* **euros.**

In the below box the characteristics of your trip performed on *MODO (underscored)* **are recalled:**

- **In-vehicle travel time, excluding possible intermediate stops:** *TEMPO* **minutes**
- **Waiting time:** *ATTESA* **minutes**
- **Walking time:** *MARCIA* **minutes**
- **Total cost (fuel, tolls, parking costs, tickets):** *COSTO* **euros (based on your answers).**

SWITCH_TAXI TP Independently on what you reported in the previous question, please imagine that you can use an <u>on-demand transportation service</u> to perform the same trip, booking the ride, but travelling with other passengers.

If you had to perform the same trip again in the future, what would be your propensity to use this new service with travel characteristics explained below, instead of the mode or modes that you currently adopt? *Answer with five levels: "I am not at all inclined to use the switching mode", "I am not very inclined to use the switching mode", "Neutral", "I am slightly inclined to use the switching mode", "I am strongly inclined to use the switching mode".*

- **in-vehicle travel time:** *If TEMPO_SW_TAXI = 0* **"less than one minute"**, *otherwise TEMPO_SW_TAXI* **minutes**
- **waiting time at the pick up location:** *ATTESA_SW_TAXI* **minutes**
- **walking time from/to the pick up location:** *MARCIA_SW_TAXI* **minutes**
- **Total cost:** *COSTO_SW_TAXI* **euros.**

In the below box the characteristics of your trip performed on *MODO (underscored)* **are recalled:**

- **In-vehicle travel time, excluding possible intermediate stops:** *TEMPO* **minutes**
- **Waiting time:** *ATTESA* **minutes**
- **Walking time:** *MARCIA* **minutes**
- **Total cost (fuel, tolls, parking costs, tickets):** *COSTO* **euros (based on your answers).**

SWITCH_BIKE Independently on what you reported in the previous question, please imagine that you can use a bike.

If you had to perform the same trip again in the future, what would be your propensity to use this bike with travel characteristics explained below, instead of the mode or modes that you currently adopt? *Answer with five levels: "I am not at all inclined to use the switching mode", "I am not very inclined to use the switching mode", "Neutral", "I am slightly inclined to use the switching mode", "I am strongly inclined to use the switching mode".*

- **Travel time:** *If TEMPO_SW_BIKE = 0* **"less than one minute"**, *otherwise TEMPO_SW_BIKE* **minutes**
- **Walking time from/to the parking place:** *MARCIA_SW_BIKE* **minutes.**

In the below box the characteristics of your trip performed on *MODO (underscored)* **are recalled:**

- **In-vehicle travel time, excluding possible intermediate stops:** *TEMPO* **minutes**
- **Waiting time:** *ATTESA* **minutes**
- **Walking time:** *MARCIA* **minutes**
- **Total cost (fuel, tolls, parking costs, tickets):** *COSTO* **euros (based on your answers).**

SWITCH_BSHAR Independently on what you reported in the previous question, please imagine that you are a member of a bike sharing service which is suitable for your trip and you can use it. *If needed, read or show a description of bike sharing.*

If you had to perform the same trip again in the future, what would be your propensity to use this bike with travel characteristics explained below, instead of the mode or modes that you currently adopt? *Answer with five levels: "I am not at all inclined to use the switching mode", "I am not very inclined to use the switching mode", "Neutral", "I am slightly inclined to use the switching mode", "I am strongly inclined to use the switching mode".*

- **Travel time:** *If TEMPO_SW_BSHAR = 0* **"less than one minute"**, *otherwise TEMPO_SW_BSHAR* **minutes**

- **Walking time from/to the parking place:** *MARCIA_SW_BSHAR* **minutes**

- **Total cost: free.**

Go to section F.

PIEDI

The walking trip that you performed lasted *TEMPO* **minutes, without considering possible intermediate stops.**

SWITCH_CAR Please imagine that you have an available car that you can drive.

If you had to perform the same trip again in the future, what would be your propensity to use the following mode with travel characteristics explained below, instead of walking? *Answer with five levels: "I am not at all inclined to use the switching mode", "I am not very inclined to use the switching mode", "Neutral", "I am slightly inclined to use the switching mode", "I am strongly inclined to use the switching mode".*

- **In-vehicle travel time:** *If TEMPO_SW_CAR = 0* **"less than one minute"**, *otherwise TEMPO_SW_CAR* **minutes**

- **Walking time from/to the parking place:** *MARCIA_SW_CAR* **minutes**

- **Fuel and parking cost:** *COSTO_SW_CAR* **euros.**

The walking trip that you performed lasted *TEMPO* **minutes, without considering possible intermediate stops.**

SWITCH_CSHAR Independently on what you reported in the previous question, please imagine that you are a member of a car sharing service which is suitable for your trip and you can use it. *If needed, read or show a description of car sharing.*

If you had to perform the same trip again in the future, what would be your propensity to use the following mode with travel characteristics explained below, instead of walking? *Answer with five levels: "I am not at all inclined to use the switching mode", "I am not very inclined to use the switching mode", "Neutral", "I am slightly inclined to use the switching mode", "I am strongly inclined to use the switching mode".*

- **In-vehicle travel time:** *If TEMPO_SW_CSHAR = 0* **"less than one minute"**, *otherwise TEMPO_SW_CSHAR* **minutes**

- **Walking time from/to the parking place:** *MARCIA_SW_CSHAR* **minutes**

- **Total costs:** *COSTO_SW_CSHAR* **euros.**

The walking trip that you performed lasted *TEMPO* **minutes, without considering possible intermediate stops.**

SWITCH_TP Independently on what you reported in the previous question, please imagine that there is a new public transport line that you can use to perform the same trip without any transfers.

If you had to perform the same trip again in the future, what would be your propensity to use this new line with travel characteristics explained below, instead of walking? *Answer with five levels: "I am not at all inclined to use the switching mode", "I am not very inclined to use the switching mode", "Neutral", "I am slightly inclined to use the switching mode", "I am strongly inclined to use the switching mode".*

- in-vehicle travel time: *If TEMPO_SW_TP = 0* **“less than one minute”**, *otherwise TEMPO_SW_TP* **minutes**
- **Waiting time at the transit stop(s):** *ATTESA_SW_TP* **minutes**
- **walking time:** *MARCIA_SW_TP* **minutes**
- **Ticket cost:** *COSTO_SW_TP* **euros.**

The walking trip that you performed lasted *TEMPO* **minutes, without considering possible intermediate stops.**

SWITCH_TAXI Independently on what you reported in the previous question, please imagine that you can use an on-demand transportation service to perform the same trip, booking the ride, but travelling with other passengers.

If you had to perform the same trip again in the future, what would be your propensity to use this new service with travel characteristics explained below, instead of walking? *Answer with five levels: "I am not at all inclined to use the switching mode", "I am not very inclined to use the switching mode", "Neutral", "I am slightly inclined to use the switching mode", "I am strongly inclined to use the switching mode".*

- **in-vehicle travel time:** *If TEMPO_SW_TAXI = 0* **“less than one minute”**, *otherwise TEMPO_SW_TAXI* **minutes**
- **waiting time at the pick up location:** *ATTESA_SW_TAXI* **minutes**
- **walking time from/to the pick up location:** *MARCIA_SW_TAXI* **minutes**
- **Total cost:** *COSTO_SW_TAXI* **euros.**

The walking trip that you performed lasted *TEMPO* **minutes, without considering possible intermediate stops.**

SWITCH_BIKE Independently on what you reported in the previous question, please imagine that you can use a bike.

If you had to perform the same trip again in the future, what would be your propensity to use this bike with travel characteristics explained below, instead of walking? *Answer with five levels: "I am not at all inclined to use the switching mode", "I am not very inclined to use the switching mode", "Neutral", "I am slightly inclined to use the switching mode", "I am strongly inclined to use the switching mode".*

- **Travel time:** *If TEMPO_SW_BIKE = 0* **“less than one minute”**, *otherwise TEMPO_SW_BIKE* **minutes**
- **Walking time from/to the parking place:** *MARCIA_SW_BIKE* **minutes.**

The walking trip that you performed lasted *TEMPO* **minutes, without considering possible intermediate stops.**

SWITCH_BSHAR Independently on what you reported in the previous question, please imagine that you are a member of a bike sharing service which is suitable for your trip and you can use it. *If needed, read or show a description of bike sharing.*

If you had to perform the same trip again in the future, what would be your propensity to use this bike with travel characteristics explained below, instead of walking? *Answer with five levels: "I am not at all inclined to use the switching mode", "I am* *not very inclined to use the switching mode", "Neutral", "I am slightly inclined to use the switching mode", "I am strongly inclined to use the switching mode".*

- **Travel time:** *If TEMPO_SW_BSHAR = 0* **"less than one minute"**, *otherwise TEMPO_SW_BSHAR* **minutes**
- **Walking time from/to the parking place:** *MARCIA_SW_BSHAR* **minutes**
- **Total cost: free.**

Go to section F.

F. SOCIO-DEMOGRAPHIC QUESTIONS

In this last part of the interview, questions about you are posed, in order to group the answers according to your individual characteristics.

If OCCUPAZ = from 1 to 7: **SETTORE Which is or was your job sector?** *(If you are in cassa integrazione, please specify the sector)*

1. Agriculture
2. Industrial sector
3. Sales/artisanship
4. Services
5. Public administration
6. Other

STUDIO What is the highest education level you have?

1. No studies
2. Primary school
3. Middle school
4. High school
5. University degree (Bachelor, Master of Science, Doctorate)

SALUTE Do you currently have temporary or permanent health or disability issues that make it difficult for you to leave home?

1. Yes
2. No

DEAMB In the 24 hours before the interview, did you used one of the following tools to walk?

1. None
2. Stick, crutch or walker
3. Wheelchair
4. Stick or guide dog for blinded persons

5. Other

PATENTE Do you one a car driving licence?

1. Yes
2. No

PARK_CASA Do you have a reserved park near your home?

1. Yes
2. No

If OCCUPAZ = from 1 to 8: **PARK_LAV Do you have a reserved park near your school or working place?**

1. Yes
2. No

TP_ABBON Do you have a public transport pass?

1. Yes
2. No

If BIBS_S = No: **BIBS_ABBON Are you a member of a bike sharing system?**

1. Yes
2. No

If BIBS_S = No and BIBS_ABBON = Yes: **BIBS_TEMPO How long have you been a member of bike sharing?**

1. From less than one month
2. From one to six months
3. From six months to one year
4. From one to two years
5. From more than two years

If AUCS_S = No: **AUCS_ABBON Are you a member of a car sharing system (enjoy, car2go, IoGuido, blueTorino…)?**

1. Yes
2. No

If AUCS_S = No and AUCS_ABBON = Yes: **AUCS_TEMPO How long have you been a car sharing member?**

1. From less than one month
2. From one to six months
3. From six months to one year
4. From one to two years

5. From more than two years

We ask you now to consider the household unit or the people with whom you have emotional bond that are currently living with you, excluding guests or those who now live elsewhere for study or work.

FAM_N How many people, including yourself, live in your household? *Specify a number greater or equal to 1.*

FAM_LAVORO How many people in your household, including yourself, currently work? *Specify a number less or equal to FAM_N.*

FAM_PAT *If FAM_N = 1 and PATENTE = Yes, set* **FAM_PAT** *= 1,* **FAM_DIP** *= 0.* **FAM_FIGLI** *= 0*, *and go to* **FAM_AUTO**, *otherwise* **How many licensees, including yourself, are there in your household?** *Specify a number less or equal to FAM_N.*

FAM_DIP *If FAM_N > 1* **How many self-sufficient adult persons are there in your household?** *Specify a number greater than zero and less or equal FAM_N. Otherwise* **FAM_DIP** *= 0.*

FAM_FIGLI *If FAM_N > 1:* **How many children lives with you?** *Specify a number less or equal to FAM_N-1.*

Otherwise **FAM_FIGLI = 0**

FAM_MINORI *If FAM_FIGLI > 0:* **How many of them are underage?** *Specify a number less or equal to a FAM_FIGLI.*

Otherwise **FAM_MINORI = 0**

FAM_AUTO How many cars are available to your household? *Specify a number greater or equal to zero. Include company cars, rented cars and those being repaired. Do not consider cars which are definitively down.*

FAM_MOTO How many motorbikes are available to your household *Specify a number greater or equal to zero.*

FAM_REDDITO Considering the income of all members or people with whom you have emotional bond currently living with you, excluding guests or those who now live elsewhere for study or work, in which of the following ranges does the average net monthly income of your household fall?

1. Up to 400 €
2. From 401 € up to 600 €
3. From 601 € up to 800
4. From 801 € up to 1000 €
5. From 1001 € up to 1200 €
6. From 1201 € up to 1500 €
7. From 1501 € up to 1800 €
8. From 1801 € up to 2000 €
9. From 2001 € up to 2500 €
10. From 2501 € up to 3000 €
11. From 3001 € up to 4000 €
12. From 4001 € up to 6000 €
13. From 6001 € up to 10.000 €

14. More than 10.001 €

CONTATTO The interview is ended, thanks for your answers. Are you willing to participate in further travel survey in the future? *If the interviewed accepts, write the name, surname, e-mail, phone number of address.*

A.2.4 Attachment 3. Values to be assigned to variables in the section E "Stated-preferences experiments"

Stated-preferences experiments have one alternative, namely "switch", and the base option "opt-out", which corresponds to using the already adopted travel mode. The final question is a labelled experiment, where the label is the attribute "travel mode", which can be equal to the following six levels (obtained by aggregating the travel means into the six classes reported in the PREVAL question): private car, car sharing, taxi (individual or not), public transport, bike and bike sharing. In the following, the six classes are respectively labelled as: CAR, CSHAR, TAXI, TP, BICI, BSHAR.

All the alternatives have four quantitative attributes: trip cost, in-vehicle time, waiting time and walking time. These attributes are equal to COSTO, TEMPO, ATTESA and MARCIA for the opt-out alternative, whereas they can be equal to values with 3 levels (low, base and high) for the "switch" alternative. All the levels are reported in Attachment 4

Tables to assign the values to variables COSTO_SW_CAR, TEMPO_SW_CAR, MARCIA_SW_CAR, COSTO_SW_CSHAR, TEMPO_SW_CSHAR, MARCIA_SW_CSHAR, COSTO_SW_TAXI, TEMPO_SW_TAXI, ATTESA_SW_TAXI, MARCIA_SW_TAXI, COSTO_SW_TP, TEMPO_SW_TP, ATTESA_SW_TP, MARCIA_SW_TP, TEMPO_SW_BICI, MARCIA_SW_BICI, TEMPO_SW_BSHAR, MARCIA_SW_BSHAR as a function of "opt-out" alternative, according to the factorial design, are reported in the following. See Attachments 4 and 5 for further details about the definition of these values.

Functions adopted to calculate values in the following tables are reported below. "`base`" variable is replaced by the specific value of the corresponding variable each time, following the rules in the tables.

```
Thigh = base+5+ARROTONDA.MULTIPLO(base*0.15;5)+SE(O(VALORE(DESTRA(base;2))=16;VALORE(DESTRA(base;2))=46;VALORE(DESTRA(base;2))=81);1;0)+SE(VALORE(DESTRA(base;2))=17;-3;0)+SE(VALORE(DESTRA(base;2))=18;-2;0)+SE(O(VALORE(DESTRA(base;2))=19;VALORE(DESTRA(base;2))=84);-1;0)+SE(O(VALORE(DESTRA(base;2))=47;VALORE(DESTRA(base;2))=82);2;0)+SE(O(VALORE(DESTRA(base;2))=48;VALORE(DESTRA(base;2))=83);3;0)+SE(VALORE(DESTRA(base;2))=49;4;0)
Tlow = base-5-ARROTONDA.MULTIPLO(base*0.15;5)+SE(base<5;5-base;)+SE(O(VALORE(DESTRA(base;2))=16;VALORE(DESTRA(base;2))=46;VALORE(DESTRA(base;2))=81);-1;0)+SE(VALORE(DESTRA(base;2))=17;3;0)+SE(VALORE(DESTRA(base;2))=18;2;0)+SE(O(VALORE(DESTRA(base;2))=19;VALORE(DESTRA(base;2))=84);1;0)+SE(O(VALORE(DESTRA(base;2))=47;VALORE(DESTRA(base;2))=82);-2;0)+SE(O(VALORE(DESTRA(base;2))=48;VALORE(DESTRA(base;2))=83);-3;0)+SE(VALORE(DESTRA(base;2))=49;-4;0)
ChighCS = ARROTONDA(base*1.3+0.5;1)
ClowCS = MAX(0.3; SE(ARROTONDA(base/1.429-0.5;1)<0;0.3;ARROTONDA(base/1.429-0.5;1)))
CbaseBS = SE(TEMPO<=30; 0; SE(TEMPO<=60; 0.8; SE(TEMPO<=90; 2.3; SE(TEMPO<=120; 4.3; 4.3 + (2*(ARROTONDA.ECCESSO.MAT((TEMPO-120)/30;1)))))))
Chigh = ARROTONDA(base*1.3+0.5;1)
Clow = SE(ARROTONDA(base/1.429-0.5;1)<0;0;ARROTONDA(base/1.429-0.5;1))
```

Values to be assigned to variables COSTO_SW_CAR, TEMPO_SW_CAR, MARCIA_SW_CAR, COSTO_SW_CSHAR, TEMPO_SW_CSHAR, MARCIA_SW_CSHAR, COSTO_SW_TAXI, TEMPO_SW_TAXI, ATTESA_SW_TAXI, MARCIA_SW_TAXI, COSTO_SW_TP, TEMPO_SW_TP, ATTESA_SW_TP, MARCIA_SW_TP, TEMPO_SW_BICI, MARCIA_SW_BICI, TEMPO_SW_BSHAR, MARCIA_SW_BSHAR in the section E, as a function of MODO variable and of the ransom value of BLOCK variable, are reported below.

If BLOCK = 1.

If MODO = CAR

	TEMPO	ATTESA	MARCIA	COSTO
SWITCH_CAR	TEMPO_SW_CAR = THigh (baIf = TEMPO)	/ /	MARCIA_SW_CAR = THigh (baIf = MARCIA)	COSTO_SW_CAR = Clow (baIf = COSTO)
SWITCH_CSHAR	TEMPO_SW_CSHAR = Tlow (baIf = TEMPO)	/ /	MARCIA_SW_CSHAR = Tlow (baIf = MARCIA)	COSTO_SW_CSHAR = ClowCS (baIf = COSTO)
SWITCH_TP	TEMPO_SW_TP = Tlow (baIf = TEMPO)	ATTESA_SW_TP = Thigh (baIf = ATTESA)	MARCIA_SW_TP = MARCIA	COSTO_SW_TP = Chigh (baIf = COSTO)
SWITCH_TAXI	TEMPO_SW_TAXI = Thigh (baIf = TEMPO)	ATTESA_SW_TAXI = Tlow (baIf = ATTESA)	MARCIA_SW_TAXI = MARCIA	COSTO_SW_TAXI = 3.5 + COSTO
SWITCH_BIKE	TEMPO_SW_BIKE = GOO_TPI/3	/ /	MARCIA_SW_BIKE = Thigh (baIf = MARCIA)	/ /
SWITCH_BSHAR	TEMPO_SW_BSHAR = GOO_TPI/3	/ /	MARCIA_SW_BSHAR = Tlow (baIf = MARCIA)	COSTO_SW_BSHAR = Chigh (baIf = CbaseBS)

If MODO = CSHAR

	TEMPO	ATTESA	MARCIA	COSTO
SWITCH_CAR	TEMPO_SW_CAR = Tlow (baIf = TEMPO)	/ /	MARCIA_SW_CAR = Tlow (baIf = MARCIA)	COSTO_SW_CAR = Clow (baIf = COSTO)
SWITCH_CSHAR	TEMPO_SW_CSHAR = Thigh (baIf = TEMPO)	/ /	MARCIA_SW_CSHAR = Thigh (baIf = MARCIA)	COSTO_SW_CSHAR = ClowCS (baIf = COSTO)
SWITCH_TP	TEMPO_SW_TP = Tlow (baIf = TEMPO)	ATTESA_SW_TP = Thigh (baIf = ATTESA)	MARCIA_SW_TP = MARCIA	COSTO_SW_TP = Chigh (baIf = COSTO)
SWITCH_TAXI	TEMPO_SW_TAXI = Thigh (baIf = TEMPO)	ATTESA_SW_TAXI = Tlow (baIf = ATTESA)	MARCIA_SW_TAXI = MARCIA	COSTO_SW_TAXI = 3.5 + COSTO
SWITCH_BIKE	TEMPO_SW_BIKE = GOO_TPI/3	/ /	MARCIA_SW_BIKE = Thigh (baIf = MARCIA)	/ /
SWITCH_BSHAR	TEMPO_SW_BSHAR = GOO_TPI/3	/ /	MARCIA_SW_BSHAR = Tlow (baIf = MARCIA)	COSTO_SW_BSHAR = Chigh (baIf = CbaseBS)

If MODO = TP

	TEMPO	ATTESA	MARCIA	COSTO
SWITCH_CAR	TEMPO_SW_CAR = TEMPO	/ /	MARCIA_SW_CAR = Thigh (baIf = MARCIA)	COSTO_SW_CAR = COSTO
SWITCH_CSHAR	TEMPO_SW_CSHAR = Thigh (baIf = TEMPO)	/ /	MARCIA_SW_CSHAR = MARCIA	COSTO_SW_CSHAR = COSTO
SWITCH_TP	TEMPO_SW_TP = Thigh (baIf = TEMPO)	ATTESA_SW_TP = ATTESA	MARCIA_SW_TP = Thigh (baIf = MARCIA)	COSTO_SW_TP = Clow (baIf = COSTO)
SWITCH_TAXI	TEMPO_SW_TAXI = Tlow (baIf = TEMPO)	ATTESA_SW_TAXI = Tlow (baIf = ATTESA)	MARCIA_SW_TAXI = Tlow (baIf = MARCIA)	COSTO_SW_TAXI = Clow (baIf = 3.5 + COSTO)
SWITCH_BIKE	TEMPO_SW_BIKE = Tlow (baIf = GOO_TPI/3)	/ /	MARCIA_SW_BIKE = MARCIA	/ /
SWITCH_BSHAR	TEMPO_SW_BSHAR = GOO_TPI/3	/ /	MARCIA_SW_BSHAR = Tlow (baIf = MARCIA)	COSTO_SW_BSHAR = Chigh (baIf = CbaseBS)

If MODO = TAXI

	TEMPO	ATTESA	MARCIA	COSTO
SWITCH_CAR	TEMPO_SW_CAR = TEMPO	/ /	MARCIA_SW_CAR = Thigh (baIf = MARCIA)	COSTO_SW_CAR = COSTO
SWITCH_CSHAR	TEMPO_SW_CSHAR = Thigh (baIf = TEMPO)	/ /	MARCIA_SW_CSHAR = MARCIA	COSTO_SW_CSHAR = COSTO
SWITCH_TP	TEMPO_SW_TP = Tlow (baIf = TEMPO)	ATTESA_SW_TP = Tlow (baIf = ATTESA)	MARCIA_SW_TP = Tlow (baIf = MARCIA)	COSTO_SW_TP = Clow (baIf = COSTO)
SWITCH_TAXI	TEMPO_SW_TAXI = Thigh (baIf = TEMPO)	ATTESA_SW_TAXI = ATTESA	MARCIA_SW_TAXI = Thigh (baIf = MARCIA)	COSTO_SW_TAXI = Clow (baIf = 3.5 + COSTO)
SWITCH_BIKE	TEMPO_SW_BIKE = Tlow (baIf = GOO_TPI/3)	/ /	MARCIA_SW_BIKE = MARCIA	/ /
SWITCH_BSHAR	TEMPO_SW_BSHAR = GOO_TPI/3	/ /	MARCIA_SW_BSHAR = Tlow (baIf = MARCIA)	COSTO_SW_BSHAR = Chigh (baIf = CbaseBS)

If MODO = BIKE

	TEMPO	ATTESA	MARCIA	COSTO
SWITCH_CAR	TEMPO_SW_CAR = GOO_TAU	/ /	MARCIA_SW_CAR = Thigh (baIf = MARCIA)	COSTO_SW_CAR = GOO_DAU*0.20
SWITCH_CSHAR	TEMPO_SW_CSHAR = Thigh (baIf = GOO_TAU)	/ /	MARCIA_SW_CSHAR = MARCIA	COSTO_SW_CSHAR = GOO_DAU*0.20
SWITCH_TP	TEMPO_SW_TP = GOO_TAU	ATTESA_SW_TP = ATTESA	MARCIA_SW_TP = Tlow (baIf = MARCIA)	COSTO_SW_TP = Chigh (baIf = GOO_DAU * 0.20)
SWITCH_TAXI	TEMPO_SW_TAXI = Tlow (baIf = GOO_TAU)	ATTESA_SW_TAXI = Thigh (baIf = ATTESA)	MARCIA_SW_TAXI = MARCIA	COSTO_SW_TAXI = Chigh (baIf = 3.5 + GOO_DAU * 0.20)
SWITCH_BIKE	TEMPO_SW_BIKE = Thigh (baIf = TEMPO)	/ /	MARCIA_SW_BIKE = Thigh (baIf = MARCIA)	/ /
SWITCH_BSHAR	TEMPO_SW_BSHAR = Tlow (baIf = TEMPO)	/ /	MARCIA_SW_BSHAR = Tlow (baIf = MARCIA)	COSTO_SW_BSHAR = Clow (baIf = CbaseBS)

If MODO = BSHAR

	TEMPO	ATTESA	MARCIA	COSTO
SWITCH_CAR	TEMPO_SW_CAR = GOO_TAU	/ /	MARCIA_SW_CAR = Thigh (baIf = MARCIA)	COSTO_SW_CAR = GOO_DAU *0.20
SWITCH_CSHAR	TEMPO_SW_CSHAR = Thigh (baIf = GOO_TAU)	/ /	MARCIA_SW_CSHAR = MARCIA	COSTO_SW_CSHAR = GOO_DAU *0.20
SWITCH_TP	TEMPO_SW_TP = GOO_TAU	ATTESA_SW_TP = ATTESA	MARCIA_SW_TP = Tlow (baIf = MARCIA)	COSTO_SW_TP = Chigh (baIf = GOO_DAU *0.20)
SWITCH_TAXI	TEMPO_SW_TAXI = Tlow (baIf = GOO_TAU)	ATTESA_SW_TAXI = Thigh (baIf = ATTESA)	MARCIA_SW_TAXI = MARCIA	COSTO_SW_TAXI = Chigh (baIf = 3.5 + GOO_DAU * 0.20)
SWITCH_BIKE	TEMPO_SW_BIKE = Tlow (baIf = TEMPO)	/ /	MARCIA_SW_BIKE = Tlow (baIf = MARCIA)	/ /
SWITCH_BSHAR	TEMPO_SW_BSHAR = Thigh (baIf = TEMPO)	/ /	MARCIA_SW_BSHAR = Thigh (baIf = MARCIA)	COSTO_SW_BSHAR = Clow (baIf = CbaseBS)

If MODO = PIEDI

	TEMPO	ATTESA	MARCIA	COSTO
SWITCH_CAR	TEMPO_SW_CAR = Thigh (baIf = GOO_TAU)	/ /	MARCIA_SW_CAR = TEMPO/2	COSTO_SW_CAR = GOO_DAU *0.20
SWITCH_CSHAR	TEMPO_SW_CSHAR = Tlow (baIf = GOO_TAU)	/ /	MARCIA_SW_CSHAR = TEMPO/2	COSTO_SW_CSHAR = ChighCS (baIf = GOO_DAU *0.20)
SWITCH_TP	TEMPO_SW_TP = Thigh (baIf = GOO_TAU)	ATTESA_SW_TP = ATTESA	MARCIA_SW_TP = Thigh (baIf = TEMPO/2)	COSTO_SW_TP = Clow (baIf = GOO_DAU *0.20)
SWITCH_TAXI	TEMPO_SW_TAXI = GOO_TAU	ATTESA_SW_TAXI = ATTESA	MARCIA_SW_TAXI = Tlow (baIf = TEMPO/2)	COSTO_SW_TAXI = Chigh (baIf = 3.5 + GOO_DAU * 0.20)
SWITCH_BIKE	TEMPO_SW_BIKE = Tlow (baIf = GOO_TPI/3)	/ /	MARCIA_SW_BIKE = Tlow (baIf = TEMPO/2)	/ /
SWITCH_BSHAR	TEMPO_SW_BSHAR = GOO_TPI/3	/ /	MARCIA_SW_BSHAR = Thigh (baIf = TEMPO/2)	COSTO_SW_BSHAR = CbaseBS

<u>If BLOCK = 2</u>

If MODO = CAR

	TEMPO	ATTESA	MARCIA	COSTO
SWITCH_CAR	TEMPO_SW_CAR = Tlow (baIf = TEMPO)	/ /	MARCIA_SW_CAR = Tlow (baIf = MARCIA)	COSTO_SW_CAR = COSTO
SWITCH_CSHAR	TEMPO_SW_CSHAR = TEMPO	/ /	MARCIA_SW_CSHAR = MARCIA	COSTO_SW_CSHAR = COSTO
SWITCH_TP	TEMPO_SW_TP = TEMPO	ATTESA_SW_TP = Tlow (baIf = ATTESA)	MARCIA_SW_TP = Thigh (baIf = MARCIA)	COSTO_SW_TP = Clow (baIf = COSTO)
SWITCH_TAXI	TEMPO_SW_TAXI = Tlow (baIf = TEMPO)	ATTESA_SW_TAXI = ATTESA	MARCIA_SW_TAXI = Thigh (baIf = MARCIA)	COSTO_SW_TAXI = Chigh (baIf = 3.5 + COSTO)
SWITCH_BIKE	TEMPO_SW_BIKE = Thigh (baIf = GOO_TPI/3)	/ /	MARCIA_SW_BIKE = Tlow (baIf = MARCIA)	/ /
SWITCH_BSHAR	TEMPO_SW_BSHAR = Thigh (baIf = GOO_TPI/3)	/ /	MARCIA_SW_BSHAR = MARCIA	COSTO_SW_BSHAR = Clow (baIf = CbaseBS)

If MODO = CSHAR

	TEMPO	ATTESA	MARCIA	COSTO
SWITCH_CAR	TEMPO_SW_CAR = TEMPO	/ /	MARCIA_SW_CAR = MARCIA	COSTO_SW_CAR = COSTO
SWITCH_CSHAR	TEMPO_SW_CSHAR = Tlow (baIf = TEMPO)	/ /	MARCIA_SW_CSHAR = Tlow (baIf = MARCIA)	COSTO_SW_CSHAR = COSTO
SWITCH_TP	TEMPO_SW_TP = TEMPO	ATTESA_SW_TP = Tlow (baIf = ATTESA)	MARCIA_SW_TP = Thigh (baIf = MARCIA)	COSTO_SW_TP = Clow (baIf = COSTO)
SWITCH_TAXI	TEMPO_SW_TAXI = Tlow (baIf = TEMPO)	ATTESA_SW_TAXI = ATTESA	MARCIA_SW_TAXI = Thigh (baIf = MARCIA)	COSTO_SW_TAXI = Chigh (baIf = 3.5 + COSTO)
SWITCH_BIKE	TEMPO_SW_BIKE = Thigh (baIf = GOO_TPI/3)	/ /	MARCIA_SW_BIKE = Tlow (baIf = MARCIA)	/ /
SWITCH_BSHAR	TEMPO_SW_BSHAR = Thigh (baIf = GOO_TPI/3)	/ /	MARCIA_SW_BSHAR = MARCIA	COSTO_SW_BSHAR = Clow (baIf = CbaseBS)

If MODO = TP

	TEMPO	ATTESA	MARCIA	COSTO
SWITCH_CAR	TEMPO_SW_CAR = Thigh (baIf = TEMPO)	/ /	MARCIA_SW_CAR = Tlow (baIf = MARCIA)	COSTO_SW_CAR = Chigh (baIf = COSTO)
SWITCH_CSHAR	TEMPO_SW_CSHAR = Tlow (baIf = TEMPO)	/ /	MARCIA_SW_CSHAR = Thigh (baIf = MARCIA)	COSTO_SW_CSHAR = ChighCS (baIf = COSTO)
SWITCH_TP	TEMPO_SW_TP = Tlow (baIf = TEMPO)	ATTESA_SW_TP = Thigh (baIf = ATTESA)	MARCIA_SW_TP = Tlow (baIf = MARCIA)	COSTO_SW_TP = COSTO
SWITCH_TAXI	TEMPO_SW_TAXI = TEMPO	ATTESA_SW_TAXI = ATTESA	MARCIA_SW_TAXI = MARCIA	COSTO_SW_TAXI = 3.5 + COSTO
SWITCH_BIKE	TEMPO_SW_BIKE = GOO_TPI/3	/ /	MARCIA_SW_BIKE = Thigh (baIf = MARCIA)	/ /
SWITCH_BSHAR	TEMPO_SW_BSHAR = Thigh (baIf = GOO_TPI/3)	/ /	MARCIA_SW_BSHAR = MARCIA	COSTO_SW_BSHAR = Clow (baIf = CbaseBS)

If MODO = TAXI

	TEMPO	ATTESA	MARCIA	COSTO
SWITCH_CAR	TEMPO_SW_CAR = Thigh (baIf = TEMPO)	/ /	MARCIA_SW_CAR = Tlow (baIf = MARCIA)	COSTO_SW_CAR = Chigh (baIf = COSTO)
SWITCH_CSHAR	TEMPO_SW_CSHAR = Tlow (baIf = TEMPO)	/ /	MARCIA_SW_CSHAR = Thigh (baIf = MARCIA)	COSTO_SW_CSHAR = ChighCS (baIf = COSTO)
SWITCH_TP	TEMPO_SW_TP = TEMPO	ATTESA_SW_TP = ATTESA	MARCIA_SW_TP = MARCIA	COSTO_SW_TP = COSTO
SWITCH_TAXI	TEMPO_SW_TAXI = Tlow (baIf = TEMPO)	ATTESA_SW_TAXI = Thigh (baIf = ATTESA)	MARCIA_SW_TAXI = Tlow (baIf = MARCIA)	COSTO_SW_TAXI = 3.5 + COSTO
SWITCH_BIKE	TEMPO_SW_BIKE = GOO_TPI/3	/ /	MARCIA_SW_BIKE = Thigh (baIf = MARCIA)	/ /
SWITCH_BSHAR	TEMPO_SW_BSHAR = Thigh (baIf = GOO_TPI/3)	/ /	MARCIA_SW_BSHAR = MARCIA	COSTO_SW_BSHAR = Clow (baIf = CbaseBS)

If MODO = BIKE

	TEMPO	ATTESA	MARCIA	COSTO
SWITCH_CAR	TEMPO_SW_CAR = Thigh (baIf = GOO_TAU)	/ /	MARCIA_SW_CAR = Tlow (baIf = MARCIA)	COSTO_SW_CAR = Chigh (baIf = GOO_DAU * 0.20)
SWITCH_CSHAR	TEMPO_SW_CSHAR = Tlow (baIf = GOO_TAU)	/ /	MARCIA_SW_CSHAR = Thigh (baIf = MARCIA)	COSTO_SW_CSHAR = ChighCS (baIf = GOO_DAU * 0.20)
SWITCH_TP	TEMPO_SW_TP = Thigh (baIf = GOO_TAU)	ATTESA_SW_TP = Thigh (baIf = ATTESA)	MARCIA_SW_TP = MARCIA	COSTO_SW_TP = Clow (baIf = GOO_DAU * 0.20)
SWITCH_TAXI	TEMPO_SW_TAXI = GOO_TAU	ATTESA_SW_TAXI = Tlow (baIf = ATTESA)	MARCIA_SW_TAXI = Thigh (baIf = MARCIA)	COSTO_SW_TAXI = Clow (baIf = 3.5 + GOO_DAU * 0.20)
SWITCH_BIKE	TEMPO_SW_BIKE = Tlow (baIf = TEMPO)	/ /	MARCIA_SW_BIKE = Tlow (baIf = MARCIA)	/ /
SWITCH_BSHAR	TEMPO_SW_BSHAR = TEMPO	/ /	MARCIA_SW_BSHAR = MARCIA	COSTO_SW_BSHAR = CbaseBS

If MODO = BSHAR

	TEMPO	ATTESA	MARCIA	COSTO
SWITCH_CAR	TEMPO_SW_CAR = Thigh (baIf = GOO_TAU)	/ /	MARCIA_SW_CAR = Tlow (baIf = MARCIA)	COSTO_SW_CAR = Chigh (baIf = GOO_DAU * 0.20)
SWITCH_CSHAR	TEMPO_SW_CSHAR = Tlow (baIf = GOO_TAU)	/ /	MARCIA_SW_CSHAR = Thigh (baIf = MARCIA)	COSTO_SW_CSHAR = ChighCS (baIf = GOO_DAU * 0.20)
SWITCH_TP	TEMPO_SW_TP = Thigh (baIf = GOO_TAU)	ATTESA_SW_TP = Thigh (baIf = ATTESA)	MARCIA_SW_TP = MARCIA	COSTO_SW_TP = Clow (baIf = GOO_DAU * 0.20)
SWITCH_TAXI	TEMPO_SW_TAXI = GOO_TAU	ATTESA_SW_TAXI = Tlow (baIf = ATTESA)	MARCIA_SW_TAXI = Thigh (baIf = MARCIA)	COSTO_SW_TAXI = Clow (baIf = 3.5 + GOO_DAU * 0.20)
SWITCH_BIKE	TEMPO_SW_BIKE = TEMPO	/ /	MARCIA_SW_BIKE = MARCIA	/ /
SWITCH_BSHAR	TEMPO_SW_BSHAR = Tlow (baIf = TEMPO)	/ /	MARCIA_SW_BSHAR = Tlow (baIf = MARCIA)	COSTO_SW_BSHAR = CbaseBS

If MODO = PIEDI

	TEMPO	ATTESA	MARCIA	COSTO
SWITCH_CAR	TEMPO_SW_CAR = Tlow (baIf = GOO_TAU)	/ /	MARCIA_SW_CAR = Thigh (baIf = TEMPO/2)	COSTO_SW_CAR = Chigh (baIf = GOO_DAU * 0.20)
SWITCH_CSHAR	TEMPO_SW_CSHAR = GOO_TAU	/ /	MARCIA_SW_CSHAR = Thigh (baIf = TEMPO/2)	COSTO_SW_CSHAR = ClowCS (baIf = GOO_DAU * 0.20)
SWITCH_TP	TEMPO_SW_TP = Tlow (baIf = GOO_TAU)	ATTESA_SW_TP = Thigh (baIf = ATTESA)	MARCIA_SW_TP = Tlow (baIf = TEMPO/2)	COSTO_SW_TP = GOO_DAU * 0.20
SWITCH_TAXI	TEMPO_SW_TAXI = Thigh (baIf = GOO_TAU)	ATTESA_SW_TAXI = Thigh (baIf = ATTESA)	MARCIA_SW_TAXI = TEMPO/2	COSTO_SW_TAXI = Clow (baIf = 3.5 + GOO_DAU * 0.20)
SWITCH_BIKE	TEMPO_SW_BIKE = GOO_TPI/3	/ /	MARCIA_SW_BIKE = TEMPO/2	/ /
SWITCH_BSHAR	TEMPO_SW_BSHAR = Thigh (baIf = GOO_TPI/3)	/ /	MARCIA_SW_BSHAR = Tlow (baIf = TEMPO/2)	COSTO_SW_BSHAR = Chigh (baIf = CbaseBS)

If BLOCK = 3.

If MODO = CAR

	TEMPO	ATTESA	MARCIA	COSTO
SWITCH_CAR	TEMPO_SW_CAR = TEMPO	/ /	MARCIA_SW_CAR = MARCIA	COSTO_SW_CAR = Chigh (baIf = COSTO)
SWITCH_CSHAR	TEMPO_SW_CSHAR = Thigh (baIf = TEMPO)	/ /	MARCIA_SW_CSHAR = Thigh (baIf = MARCIA)	COSTO_SW_CSHAR = ChighCS (baIf = COSTO)
SWITCH_TP	TEMPO_SW_TP = Thigh (baIf = TEMPO)	ATTESA_SW_TP = ATTESA	MARCIA_SW_TP = Tlow (baIf = MARCIA)	COSTO_SW_TP = COSTO
SWITCH_TAXI	TEMPO_SW_TAXI = TEMPO	ATTESA_SW_TAXI = Thigh (baIf = ATTESA)	MARCIA_SW_TAXI = Tlow (baIf = MARCIA)	COSTO_SW_TAXI = Clow (baIf = 3.5+ COSTO)
SWITCH_BIKE	TEMPO_SW_BIKE = Tlow (baIf = GOO_TPI/3)	/ /	MARCIA_SW_BIKE = MARCIA	/ /
SWITCH_BSHAR	TEMPO_SW_BSHAR = Tlow (baIf = GOO_TPI/3)	/ /	MARCIA_SW_BSHAR = Thigh (baIf = MARCIA)	COSTO_SW_BSHAR = CbaseBS

If MODO = CSHAR

	TEMPO	ATTESA	MARCIA	COSTO
SWITCH_CAR	TEMPO_SW_CAR = Thigh (baIf = TEMPO)	/ /	MARCIA_SW_CAR = Thigh (baIf = MARCIA)	COSTO_SW_CAR = Chigh (baIf = COSTO)
SWITCH_CSHAR	TEMPO_SW_CSHAR = TEMPO	/ /	MARCIA_SW_CSHAR = MARCIA	COSTO_SW_CSHAR = ChighCS (baIf = COSTO)
SWITCH_TP	TEMPO_SW_TP = Thigh (baIf = TEMPO)	ATTESA_SW_TP = ATTESA	MARCIA_SW_TP = Tlow (baIf = MARCIA)	COSTO_SW_TP = COSTO
SWITCH_TAXI	TEMPO_SW_TAXI = TEMPO	ATTESA_SW_TAXI = Thigh (baIf = ATTESA)	MARCIA_SW_TAXI = Tlow (baIf = MARCIA)	COSTO_SW_TAXI = Clow (baIf = 3.5 + COSTO)
SWITCH_BIKE	TEMPO_SW_BIKE = Tlow (baIf = GOO_TPI/3)	/ /	MARCIA_SW_BIKE = Tlow (baIf = MARCIA)	/ /
SWITCH_BSHAR	TEMPO_SW_BSHAR = Tlow (baIf = GOO_TPI/3)	/ /	MARCIA_SW_BSHAR = Thigh (baIf = MARCIA)	COSTO_SW_BSHAR = CbaseBS

If MODO = TP

	TEMPO	ATTESA	MARCIA	COSTO
SWITCH_CAR	TEMPO_SW_CAR = Tlow (baIf = TEMPO)	/ /	MARCIA_SW_CAR = MARCIA	COSTO_SW_CAR = Clow (baIf = COSTO)
SWITCH_CSHAR	TEMPO_SW_CSHAR = TEMPO	/ /	MARCIA_SW_CSHAR = Tlow (baIf = MARCIA)	COSTO_SW_CSHAR = ClowCS (baIf = COSTO)
SWITCH_TP	TEMPO_SW_TP = TEMPO	ATTESA_SW_TP = Tlow (baIf = ATTESA)	MARCIA_SW_TP = MARCIA	COSTO_SW_TP = Chigh (baIf = COSTO)
SWITCH_TAXI	TEMPO_SW_TAXI = Thigh (baIf = TEMPO)	ATTESA_SW_TAXI = Thigh (baIf = ATTESA)	MARCIA_SW_TAXI = Thigh (baIf = MARCIA)	COSTO_SW_TAXI = Chigh (baIf = 3.5 + COSTO)
SWITCH_BIKE	TEMPO_SW_BIKE = Thigh (baIf = GOO_TPI/3)	/ /	MARCIA_SW_BIKE = Tlow (baIf = MARCIA)	/ /
SWITCH_BSHAR	TEMPO_SW_BSHAR = Tlow (baIf = GOO_TPI/3)	/ /	MARCIA_SW_BSHAR = Thigh (baIf = MARCIA)	COSTO_SW_BSHAR = CbaseBS

If MODO = TAXI

	TEMPO	ATTESA	MARCIA	COSTO
SWITCH_CAR	TEMPO_SW_CAR = Tlow (baIf = TEMPO)	/ /	MARCIA_SW_CAR = MARCIA	COSTO_SW_CAR = Clow (baIf = COSTO)
SWITCH_CSHAR	TEMPO_SW_CSHAR = TEMPO	/ /	MARCIA_SW_CSHAR = Tlow (baIf = MARCIA)	COSTO_SW_CSHAR = ClowCS (baIf = COSTO)
SWITCH_TP	TEMPO_SW_TP = Thigh (baIf = TEMPO)	ATTESA_SW_TP = Thigh (baIf = ATTESA)	MARCIA_SW_TP = Thigh (baIf = MARCIA)	COSTO_SW_TP = Chigh (baIf = COSTO)
SWITCH_TAXI	TEMPO_SW_TAXI = TEMPO	ATTESA_SW_TAXI = Tlow (baIf = ATTESA)	MARCIA_SW_TAXI = MARCIA	COSTO_SW_TAXI = Chigh (baIf = 3.5 + COSTO)
SWITCH_BIKE	TEMPO_SW_BIKE = Thigh (baIf = GOO_TPI/3)	/ /	MARCIA_SW_BIKE = Tlow (baIf = MARCIA)	/ /
SWITCH_BSHAR	TEMPO_SW_BSHAR = Tlow (baIf = GOO_TPI/3)	/ /	MARCIA_SW_BSHAR = Thigh (baIf = MARCIA)	COSTO_SW_BSHAR = CbaseBS

If MODO = BIKE

	TEMPO	ATTESA	MARCIA	COSTO
SWITCH_CAR	TEMPO_SW_CAR = Tlow (baIf = GOO_TAU)	/ /	MARCIA_SW_CAR = MARCIA	COSTO_SW_CAR = Clow (baIf = GOO_DAU * 0.20)
SWITCH_CSHAR	TEMPO_SW_CSHAR = TEMPO	/ /	MARCIA_SW_CSHAR = Tlow (baIf = MARCIA)	COSTO_SW_CSHAR = ClowCS (baIf = GOO_DAU * 0.20)
SWITCH_TP	TEMPO_SW_TP = Tlow (baIf = GOO_TAU)	ATTESA_SW_TP = Tlow (baIf = ATTESA)	MARCIA_SW_TP = Thigh (baIf = MARCIA)	COSTO_SW_TP = GOO_DAU * 0.20
SWITCH_TAXI	TEMPO_SW_TAXI = Thigh (baIf = GOO_TAU)	ATTESA_SW_TAXI = ATTESA	MARCIA_SW_TAXI = Tlow (baIf = MARCIA)	COSTO_SW_TAXI = 3.5 + GOO_DAU * 0.20
SWITCH_BIKE	TEMPO_SW_BIKE = TEMPO	/ /	MARCIA_SW_BIKE = MARCIA	/ /
SWITCH_BSHAR	TEMPO_SW_BSHAR = Thigh (baIf = TEMPO)	/ /	MARCIA_SW_BSHAR = Thigh (baIf = MARCIA)	COSTO_SW_BSHAR = Chigh (baIf = CbaseBS)

If MODO = BSHAR

	TEMPO	ATTESA	MARCIA	COSTO
SWITCH_CAR	TEMPO_SW_CAR = Tlow (baIf = GOO_TAU)	/ /	MARCIA_SW_CAR = MARCIA	COSTO_SW_CAR = Clow (baIf = GOO_DAU * 0.20)
SWITCH_CSHAR	TEMPO_SW_CSHAR = GOO_TAU	/ /	MARCIA_SW_CSHAR = Tlow (baIf = MARCIA)	COSTO_SW_CSHAR = ClowCS (baIf = GOO_DAU * 0.20
SWITCH_TP	TEMPO_SW_TP = Tlow (baIf = GOO_TAU)	ATTESA_SW_TP = Tlow (baIf = ATTESA)	MARCIA_SW_TP = Thigh (baIf = MARCIA)	COSTO_SW_TP = GOO_DAU * 0.20
SWITCH_TAXI	TEMPO_SW_TAXI = Thigh (baIf = GOO_TAU)	ATTESA_SW_TAXI = ATTESA	MARCIA_SW_TAXI = Tlow (baIf = MARCIA)	COSTO_SW_TAXI = 3.5 + GOO_DAU * 0.20
SWITCH_BIKE	TEMPO_SW_BIKE = Thigh (baIf = TEMPO)	/ /	MARCIA_SW_BIKE = Thigh (baIf = MARCIA)	/ /
SWITCH_BSHAR	TEMPO_SW_BSHAR = TEMPO	/ /	MARCIA_SW_BSHAR = MARCIA	COSTO_SW_BSHAR = Chigh (baIf = CbaseBS)

If MODO = PIEDI

	TEMPO	ATTESA	MARCIA	COSTO
SWITCH_CAR	TEMPO_SW_CAR = GOO_TAU	/ /	MARCIA_SW_CAR = Tlow (baIf = TEMPO/2)	COSTO_SW_CAR = Clow (baIf = GOO_DAU * 0.20)
SWITCH_CSHAR	TEMPO_SW_CSHAR = Thigh (baIf = GOO_TAU)	/ /	MARCIA_SW_CSHAR = Tlow (baIf = TEMPO/2)	COSTO_SW_CSHAR = GOO_DAU * 0.20
SWITCH_TP	TEMPO_SW_TP = GOO_TAU	ATTESA_SW_TP = Tlow (baIf = ATTESA)	MARCIA_SW_TP = TEMPO/2	COSTO_SW_TP = Chigh (baIf = GOO_DAU * 0.20)
SWITCH_TAXI	TEMPO_SW_TAXI = Tlow (baIf = GOO_TAU)	ATTESA_SW_TAXI = Tlow (baIf = ATTESA)	MARCIA_SW_TAXI = Thigh (baIf = TEMPO/2)	COSTO_SW_TAXI = 3.5 + GOO_DAU * 0.20
SWITCH_BIKE	TEMPO_SW_BIKE = Thigh (baIf = GOO_TPI/3)	/ /	MARCIA_SW_BIKE = Thigh (baIf = TEMPO/2)	/ /
SWITCH_BSHAR	TEMPO_SW_BSHAR = Tlow (baIf = GOO_TPI/3)	/ /	MARCIA_SW_BSHAR = TEMPO/2	COSTO_SW_BSHAR = Clow (baIf = CbaseBS)

A.2.5 Attachment 4. Values of quantitative attributes of “switch” alternative in the Stated-preferences experiments

The Stated-preferences experiment has one alternative, namely “switch”, and the base option “opt-out”, which corresponds to using the already adopted travel mode. The final question is a labelled experiment, where the label is the attribute “travel mode”, which can be equal to the following six levels (obtained by aggregating the travel means into the six classes reported in the PREVAL question): private car, car sharing, taxi (individual or not), public transport, bike and bike sharing. All the alternatives have four quantitative attributes: trip cost (“cost”), in-vehicle time (“time”), waiting time (“wait”) and walking time (“feet”). These attributes are equal to COSTO, TEMPO, ATTESA and MARCIA for the opt-out alternative, whereas they can be equal to values with 3 levels (low, base and high) for the “switch” alternative.

<u>Base level for the “switch” alternative</u>

"Cost"

- The base level for "Cost" attribute is equal to **COSTO**, i.e. the estimated cost of the “opt-out" alternative, If "Switch" is referred to: private car, car sharing, public transport and if in the “opt-out” alternative motorized means have been used.
- The base level for "Cost" attribute is equal to **3,50€ + COSTO** If "Switch" alternative is referred to taxi and if in the “opt-out” alternative motorized means have been used.
- The base level for "Cost" attribute is equal to **GOO_DAU * 0,20€/km** If "Switch" is referred to: private car, car sharing, public transport and if in the “opt-out” alternative motorized means have not been used.
- The base level for "Cost" attribute is equal to **3,50€ + GOO_DAU * 0,20€/km** If "Switch" alternative is referred to taxi and if in the “opt-out” alternative motorized means have not been used.
- The base level for "Cost" attribute is equal to **0** If "Switch" is referred to bike.
- The base level for "Cost" attribute is equal to **CbaseBS**, If "Switch" is referred to bike sharing, with:
  ```
  CbaseBS = SE(TEMPO<=30;0;SE(TEMPO<=60;0.8;SE(TEMPO<=90;2.3;SE(TEMPO<=120;4.3;4.3+(2*(ARROTONDA.ECCESSO.MAT((TEMPO-120)/30;1)))))))
  ```

"Time"

- The base level for "Time" attribute is equal to **TEMPO**, i.e. the travel time for the "opt-out" alternative, If "Switch" private car, car sharing, public transport, taxi and if in the “opt-out” alternative motorized means have been used.
- The base level for "Time" attribute is equal to **GOO_TAU** If "Switch" private car, car sharing, public transport, taxi and if in the “opt-out” alternative motorized means have not been used.
- The base level for "Time" attribute is equal to **TEMPO**, i.e. the travel time for the "opt-out" alternative, If "Switch" is referred to: bike, bike sharing, and if in the “opt-out” alternative motorized means have not been used and MODO <> "PIEDI".

- The base level for "Time" attribute is equal to **GOO_TPI / 3**, If If "Switch" is referred to: bike, bike sharing, and if in the “opt-out” alternative motorized means have been used, or, since they have been used, MODO = "PIEDI".
  "Feet"
- The base level for "Feet" attribute is equal to **MARCIA**, i.e. the walking time for the "opt-out" alternative, if in the “opt-out” alternative motorized means have been used or MODO = "BIKE" or "BSHAR".
- The base level for "Feet" attribute is equal to **TEMPO /** , if in the “opt-out” alternative motorized means have not been used and MODO = "PIEDI".
  "Wait"
- The base level for "Wait" attribute is equal to **0** If "Switch" alternative is referred to: private car, car sharing, bike, bike sharing.
- The base level for "Wait" attribute is equal to **ATTESA**, i.e. the waiting time of the “opt-out” alternative, if “switch” alternative is referred to: public transport, taxi.

<u>Low and high levels for the “switch” alternative</u>

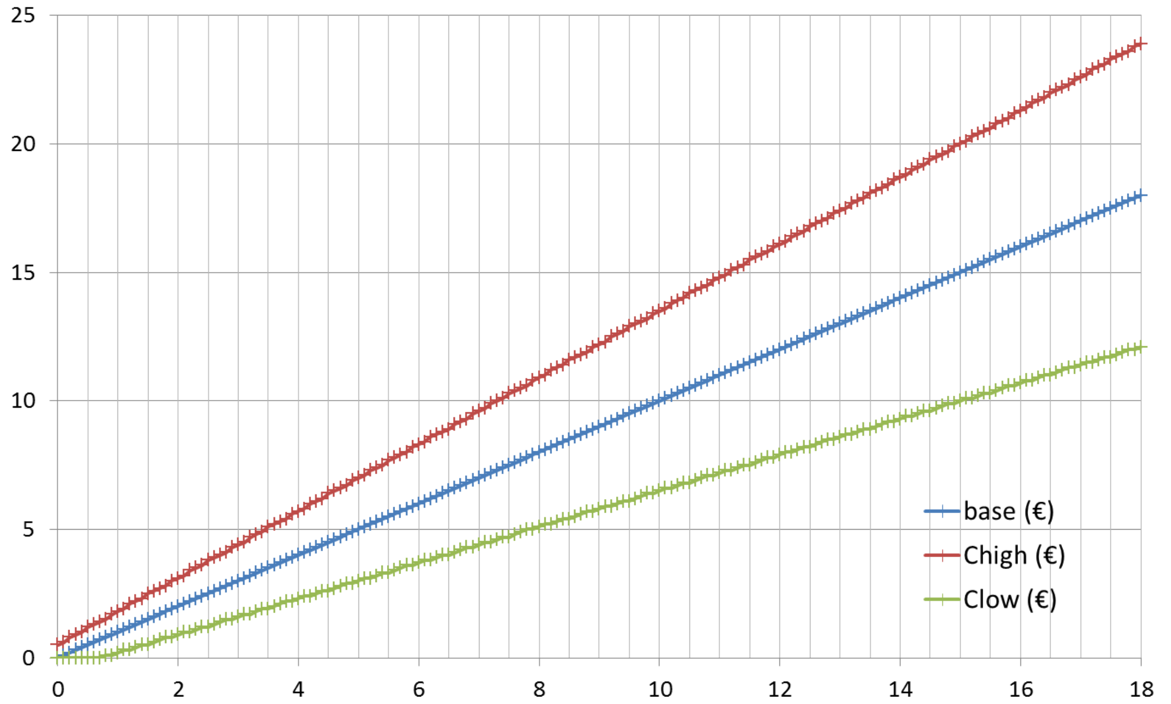
The following rules must be adopted to calculate the low and high levels fo the corresponding values of the base level of the four attributes.
"Cost"

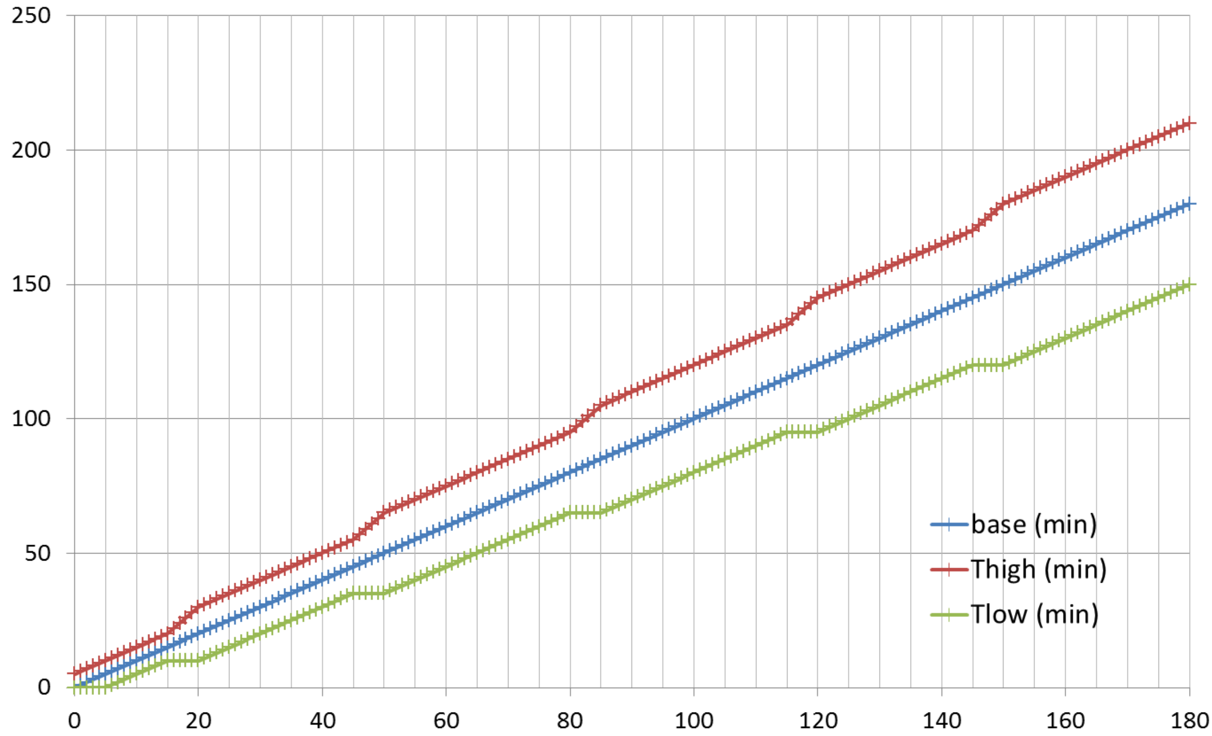
- “Low” and “high” levels for the "Cost" attribute are equal to **0** If "Switch" alternative is referred to bike.
- “Low” and “high” levels for the "Cost" attribute are equal to **Chigh** and **Clow**, respectively, If "Switch" alternative is referred to: private car, public transport, taxi, bike sharing. Values of **Chigh** and **Clow** are calculated as a function of the value of the base level following the Excel functions below:
  ```
  Chigh = ARROTONDA(base*1.3+0.5;1)
  Clow = SE(ARROTONDA(base/1.429-0.5;1)<0;0;ARROTONDA(base/1.429-0.5;1))
  ```
- “Low” and “high” levels for the "Cost" attribute are equal to **Chigh** and **Clow**, respectively, If "Switch" alternative is referred to car sharing. Values of **Chigh** and **Clow** are calculated as a function of the value of the base level following the Excel functions below:
  ```
  ChighCS = ARROTONDA(base*1.3+0.5;1)
  ClowCS = MAX(0.3; SE(ARROTONDA(base/1.429-0.5;1)<0;0.3;ARROTONDA(base/1.429-0.5;1)))
  ```

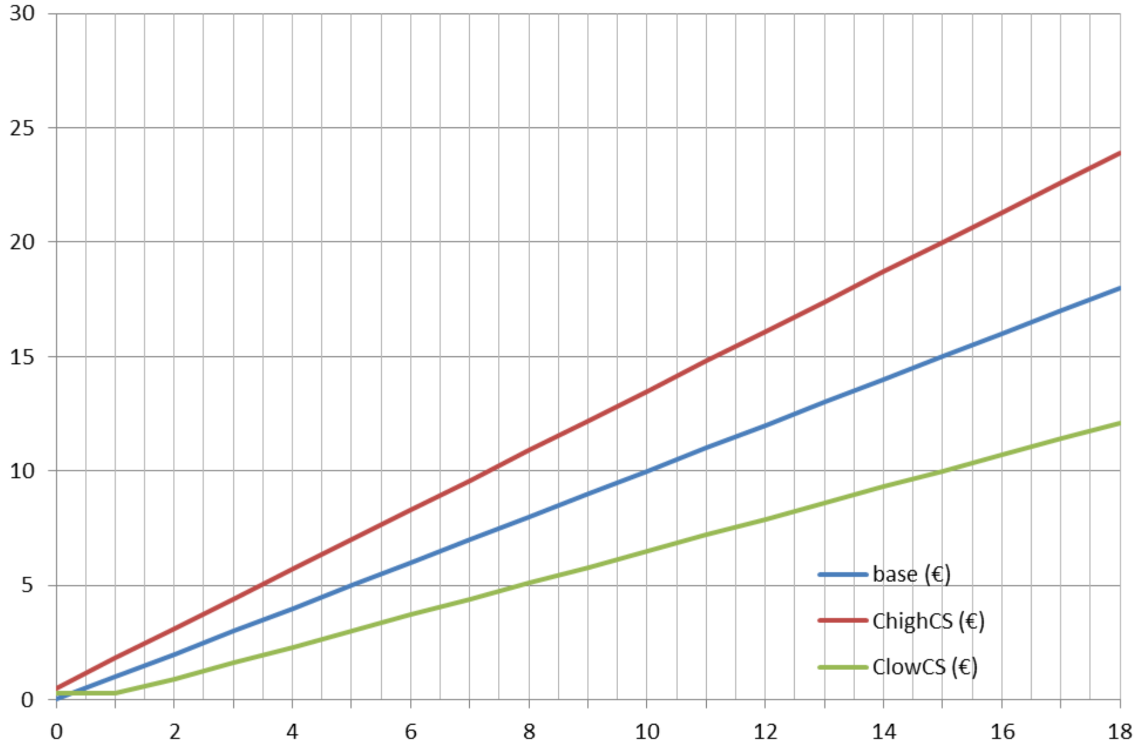
"Time”, “Feet” and “Wait”

- “Low” and “high” levels for the "Wait" attribute are equal to **0** If "Switch" alternative is referred to: private car, car sharing, bike, bike sharing.
- “Low” and “high” levels for the "Wait" attribute are equal to **Thigh** e **Tlow** If "Switch" alternative is referred to: public transport, taxi. “High” and “low” levels for "Time" and “Feet” attributes are always equal to **Thigh** e **Tlow**. Values of **Thigh** and **Tlow** are calculated as a function of the value of the base level following the Excel functions below, which are defined as piecewise functions, in order to avoid that, if the base level is a multiple of 5, “low” and “high” level should not be multiple, as well:

```
Thigh = base+5+ARROTONDA.MULTIPLO(base*0.15;5)+SE(O(VALORE(DESTRA(base;2))=16;VALORE(DESTRA(base;2))=46;VALORE(DESTRA(base;2))=81);1;0)+SE(VALORE(DESTRA(base;2))=17;-3;0)+SE(VALORE(DESTRA(base;2))=18;-2;0)+SE(O(VALORE(DESTRA(base;2))=19;VALORE(DESTRA(base;2))=84);-1;0)+SE(O(VALORE(DESTRA(base;2))=47;VALORE(DESTRA(base;2))=82);2;0)+SE(O(VALORE(DESTRA(base;2))=48;VALORE(DESTRA(base;2))=83);3;0)+SE(VALORE(DESTRA(base;2))=49;4;0)
Tlow = base-5-ARROTONDA.MULTIPLO(base*0.15;5)+SE(base<5;5-base;)+SE(O(VALORE(DESTRA(base;2))=16;VALORE(DESTRA(base;2))=46;VALORE(DESTRA(base;2))=81);-1;0)+SE(VALORE(DESTRA(base;2))=17;3;0)+SE(VALORE(DESTRA(base;2))=18;2;0)+SE(O(VALORE(DESTRA(base;2))=19;VALORE(DESTRA(base;2))=84);1;0)+SE(O(VALORE(DESTRA(base;2))=47;VALORE(DESTRA(base;2))=82);-2;0)+SE(O(VALORE(DESTRA(base;2))=48;VALORE(DESTRA(base;2))=83);-3;0)+SE(VALORE(DESTRA(base;2))=49;-4;0)
```




base (min)
Thigh (min)
Tlow (min)
0
50
100
150
200
250
0
20
40
60
80
100
120
140
160
180


base (€)
ChighCS (€)
ClowCS (€)
0
5
10
15
20
25
30
0
2
4
6
8
10
12
14
16
18

Summary

- Attributes of "switch" alternative if motorised means have been used (MOTOR_S=Yes) and MODO = CAR, TAXI, TP:

CAR	Level = "low"	Level = "base"	Level = "high"
COSTO_SW_CAR	Clow	COSTO	Chigh
TEMPO_SW_CAR	Tlow	TEMPO	Thigh
MARCIA_SW_CAR	Tlow	MARCIA	Thigh
Wait	*Not defined, implicitly taken = 0*	*Not defined, implicitly taken = 0*	*Not defined, implicitly taken = 0*

CSHAR	Level = "low"	Level = "base"	Level = "high"
COSTO_SW_CSHAR	ClowCS	COSTO	ChighCS
TEMPO_SW_CSHAR	Tlow	TEMPO	Thigh
MARCIA_SW_CSHAR	Tlow	MARCIA	Thigh
Wait	*Not defined, implicitly taken = 0*	*Not defined, implicitly taken = 0*	*Not defined, implicitly taken = 0*

TAXI	Level = "low"	Level = "base"	Level = "high"
COSTO_SW_TAXI	Clow	3,5€ + COSTO	Chigh
TEMPO_SW_TAXI	Tlow	TEMPO	Thigh
MARCIA_SW_TAXI	Tlow	MARCIA	Thigh
ATTESA_SW_TAXI	Tlow	ATTESA	Thigh

TRANSIT	Level = "low"	Level = "base"	Level = "high"
COSTO_SW_TP	Clow	COSTO	Chigh
TEMPO_SW_TP	Tlow	TEMPO	Thigh
MARCIA_SW_TP	Tlow	MARCIA	Thigh
ATTESA_SW_TP	Tlow	ATTESA	Thigh

BIKE	Level = "low"	Level = "base"	Level = "high"
Cost	*Not defined, implicitly taken = 0*	*Not defined, implicitly taken = 0*	*Not defined, implicitly taken = 0*
TEMPO_SW_BICI	Tlow	GOO_TPI / 3	Thigh
MARCIA_SW_BICI	Tlow	MARCIA	Thigh
Wait	*Not defined, implicitly taken = 0*	*Not defined, implicitly taken = 0*	*Not defined, implicitly taken = 0*

BSHAR	Level = "low"	Level = "base"	Level = "high"
Cost	*Clow*	*CbaseBS*	*Chigh*
TEMPO_SW_BSHAR	Tlow	GOO_TPI / 3	Thigh
MARCIA_SW_BSHAR	Tlow	MARCIA	Thigh
Wait	*Not defined, implicitly taken = 0*	*Not defined, implicitly taken = 0*	*Not defined, implicitly taken = 0*

- Attributes of "switch" alternative if motorised means have not been used (MOTOR_S=No) and MODO = BIKE, BSHAR:

CAR	Level = "low"	Level = "base"	Level = "high"
COSTO_SW_CAR	Clow	GOO_DAU * 0,20€/km	Chigh
TEMPO_SW_CAR	Tlow	GOO_TAU	Thigh
MARCIA_SW_CAR	Tlow	MARCIA	Thigh
Wait	*Not defined, implicitly taken = 0*	*Not defined, implicitly taken = 0*	*Not defined, implicitly taken = 0*
CSHAR	Level = "low"	Level = "base"	Level = "high"
COSTO_SW_CSHAR	ClowCS	GOO_DAU * 0,20€/km	ChighCS
TEMPO_SW_CSHAR	Tlow	GOO_TAU	Thigh
MARCIA_SW_CSHAR	Tlow	MARCIA	Thigh
Wait	*Not defined, implicitly taken = 0*	*Not defined, implicitly taken = 0*	*Not defined, implicitly taken = 0*
TAXI	Level = "low"	Level = "base"	Level = "high"
COSTO_SW_TAXI	Clow	3,5 € + GOO_DAU * 0,20€/km	Chigh
TEMPO_SW_TAXI	Tlow	GOO_TAU	Thigh
MARCIA_SW_TAXI	Tlow	MARCIA	Thigh
ATTESA_SW_TAXI	Tlow	ATTESA	Thigh
TRANSIT	Level = "low"	Level = "base"	Level = "high"
COSTO_SW_TP	Clow	GOO_DAU * 0,20€/km	Chigh
TEMPO_SW_TP	Tlow	GOO_TAU	Thigh
MARCIA_SW_TP	Tlow	MARCIA	Thigh
ATTESA_SW_TP	Tlow	ATTESA	Thigh
BIKE	Level = "low"	Level = "base"	Level = "high"
Cost	*Not defined, implicitly taken = 0*	*Not defined, implicitly taken = 0*	*Not defined, implicitly taken = 0*
TEMPO_SW_BICI	Tlow	TEMPO	Thigh
MARCIA_SW_BICI	Tlow	MARCIA	Thigh
Wait	*Not defined, implicitly taken = 0*	*Not defined, implicitly taken = 0*	*Not defined, implicitly taken = 0*
BSHAR	Level = "low"	Level = "base"	Level = "high"
Cost	*Clow*	*CbaseBS*	*Chigh*
TEMPO_SW_BSHAR	Tlow	TEMPO	Thigh
MARCIA_SW_BSHAR	Tlow	MARCIA	Thigh
Wait	*Not defined, implicitly taken = 0*	*Not defined, implicitly taken = 0*	*Not defined, implicitly taken = 0*

- Attributes of "switch" alternative if motorised means have not been used (MOTOR_S=No) and MODO = piedi:

CAR	Level = "low"	Level = "base"	Level = "high"
COSTO_SW_CAR	Clow	GOO_DAU * 0,20€/km	Chigh
TEMPO_SW_CAR	Tlow	GOO_TAU	Thigh
MARCIA_SW_CAR	Tlow	TEMPO / 2	Thigh
Wait	*Not defined, implicitly taken = 0*	*Not defined, implicitly taken = 0*	*Not defined, implicitly taken = 0*

CSHAR	Level = "low"	Level = "base"	Level = "high"
COSTO_SW_CSHAR	ClowCS	GOO_DAU * 0,20€/km	ChighCS
TEMPO_SW_CSHAR	Tlow	GOO_TAU	Thigh
MARCIA_SW_CSHAR	Tlow	TEMPO / 2	Thigh
Wait	*Not defined, implicitly taken = 0*	*Not defined, implicitly taken = 0*	*Not defined, implicitly taken = 0*

TAXI	Level = "low"	Level = "base"	Level = "high"
COSTO_SW_TAXI	Clow	3,5 € +GOO_DAU * 0,20€/km	Chigh
TEMPO_SW_TAXI	Tlow	GOO_TAU	Thigh
MARCIA_SW_TAXI	Tlow	TEMPO / 2	Thigh
ATTESA_SW_TAXI	Tlow	ATTESA	Thigh

TRANSIT	Level = "low"	Level = "base"	Level = "high"
COSTO_SW_TP	Clow	GOO_DAU * 0,20€/km	Chigh
TEMPO_SW_TP	Tlow	GOO_TAU	Thigh
MARCIA_SW_TP	Tlow	TEMPO / 2	Thigh
ATTESA_SW_TP	Tlow	ATTESA	Thigh

BIKE	Level = "low"	Level = "base"	Level = "high"
Cost	*Not defined, implicitly taken = 0*	*Not defined, implicitly taken = 0*	*Not defined, implicitly taken = 0*
TEMPO_SW_BICI	Tlow	GOO_TPI / 3	Thigh
MARCIA_SW_BICI	Tlow	TEMPO / 2	Thigh
Wait	*Not defined, implicitly taken = 0*	*Not defined, implicitly taken = 0*	*Not defined, implicitly taken = 0*

BSHAR	Level = "low"	Level = "base"	Level = "high"
Cost	*Clow*	*CbaseBS*	*Chigh*
TEMPO_SW_BSHAR	Tlow	GOO_TPI / 3	Thigh
MARCIA_SW_BSHAR	Tlow	TEMPO / 2	Thigh
Wait	*Not defined, implicitly taken = 0*	*Not defined, implicitly taken = 0*	*Not defined, implicitly taken = 0*

A.2.6 Attachment 5. Factorial design for the Stated-preferences experiments

The package *support.CEs* of R software was used to generate an orthogonal fractional factorial design with 18 different questions divided into 3 blocks, thereby each interviewed has to face with 6 different choice tasks, one for each mode. Unless the macro-trip was performed on foot, in one of these experiments the travel mode for the "switch" alternative is equal to that of "opt-out" alternative (MODO).

<u>Script on R</u>

The script adopted to generate the factorial design is reported below.

```
library (support.CEs)

# Labelled experiment -> Use function "Lma.design"


# 1. DESIGN WHEN THE MAIN TRAVEL MODE FOR THE OPT-OUT ALTERNATIVE IS: CAR

ced1 <- Lma.design (candidate.array = NULL,
   attribute.names = list (mode = c("cshar", "bike", "taxi", "transit",
         "bshar", "car"),
         cost = c("COSTOlow", "COSTObase", "COSTOhigh"),
         time = c("TEMPOlow", "TEMPObase", "TEMPOhigh"),
         feet = c("MARCIAlow", "MARCIAbase", "MARCIAhigh"),
         wait = c("ATTESAlow", "ATTESAbase", "ATTESAhigh")),
   nalternatives = 1,
   nblocks = 3,
   row.renames = TRUE,
   seed = 432)
quest_car <- questionnaire (ced1, common = c(mode ="car", cost = "cbase", time =
   "tbase", feet ="fbase", wait = "wbase"), quote = TRUE)


# 2. DESIGN WHEN THE MAIN TRAVEL MODE FOR THE OPT-OUT ALTERNATIVE IS: CAR
SHARING

ced2 <- Lma.design (candidate.array = NULL,
   attribute.names = list (mode = c("car", "bike", "taxi", "transit", "bshar",
         "cshar"),
         cost = c("COSTOlow", "COSTObase", "COSTOhigh"),
         time = c("TEMPOlow", "TEMPObase", "TEMPOhigh"),
         feet = c("MARCIAlow", "MARCIAbase", "MARCIAhigh"),
         wait = c("ATTESAlow", "ATTESAbase", "ATTESAhigh")),
   nalternatives = 1,
   nblocks = 3,
   row.renames = TRUE,
   seed = 543)
quest_cshar <- questionnaire (ced2, common = c(mode ="cshar", cost = "cbase", time
   = "tbase", feet ="fbase", wait = "wbase"), quote = TRUE)


# 3. DESIGN WHEN THE MAIN TRAVEL MODE FOR THE OPT-OUT ALTERNATIVE IS: TAXI

ced3 <- Lma.design (candidate.array = NULL,
   attribute.names = list (mode = c("transit", "car", "cshar", "bike", "bshar",
         "taxi"),
         cost = c("COSTOlow", "COSTObase", "COSTOhigh"),
         time = c("TEMPOlow", "TEMPObase", "TEMPOhigh"),
         feet = c("MARCIAlow", "MARCIAbase", "MARCIAhigh"),
```

```
          wait = c("ATTESAlow", "ATTESAbase", "ATTESAhigh")),
      nalternatives = 1,
      nblocks = 3,
      row.renames = TRUE,
      seed = 654)
quest_taxi <- questionnaire (ced3, common = c(mode ="taxi", cost = "cbase", time
      = "tbase", feet ="fbase", wait = "wbase"), quote = TRUE)


   # 4. DESIGN WHEN THE MAIN TRAVEL MODE FOR THE OPT-OUT ALTERNATIVE IS: TRANSIT

   ced4 <- Lma.design (candidate.array = NULL,
      attribute.names = list (mode = c("taxi", "car", "cshar", "bike", "bshar",
          "transit"),
          cost = c("COSTOlow", "COSTObase", "COSTOhigh"),
          time = c("TEMPOlow", "TEMPObase", "TEMPOhigh"),
          feet = c("MARCIAlow", "MARCIAbase", "MARCIAhigh"),
          wait = c("ATTESAlow", "ATTESAbase", "ATTESAhigh")),
      nalternatives = 1,
      nblocks = 3,
      row.renames = TRUE,
      seed = 765)
quest_transit <- questionnaire (ced4, common = c(mode ="transit", cost = "cbase",
      time = "tbase", feet ="fbase", wait = "wbase"), quote = TRUE)


   # 5. DESIGN WHEN THE MAIN TRAVEL MODE FOR THE OPT-OUT ALTERNATIVE IS: BIKE

   ced5 <- Lma.design (candidate.array = NULL,
      attribute.names = list (mode = c("bshar", "car", "cshar", "taxi", "transit",
"bike"),
          cost = c("COSTOlow", "COSTObase", "COSTOhigh"),
          time = c("TEMPOlow", "TEMPObase", "TEMPOhigh"),
          feet = c("MARCIAlow", "MARCIAbase", "MARCIAhigh"),
          wait = c("ATTESAlow", "ATTESAbase", "ATTESAhigh")),
      nalternatives = 1,
      nblocks = 3,
      row.renames = TRUE,
      seed = 876)
quest_bike <- questionnaire (ced5, common = c(mode ="bike", cost = "cbase", time
      = "tbase", feet ="fbase", wait = "wbase"), quote = TRUE)


   # 6. DESIGN WHEN THE MAIN TRAVEL MODE FOR THE OPT-OUT ALTERNATIVE IS: BIKE
SHARING

   ced6 <- Lma.design (candidate.array = NULL,
      attribute.names = list (mode = c("bike", "car", "cshar", "taxi", "transit",
          "bshar"),
          cost = c("COSTOlow", "COSTObase", "COSTOhigh"),
          time = c("TEMPOlow", "TEMPObase", "TEMPOhigh"),
          feet = c("MARCIAlow", "MARCIAbase", "MARCIAhigh"),
          wait = c("ATTESAlow", "ATTESAbase", "ATTESAhigh")),
      nalternatives = 1,
      nblocks = 3,
      row.renames = TRUE,
      seed = 987)
quest_bshar <- questionnaire (ced6, common = c(mode ="bshar", cost = "cbase", time
      = "tbase", feet ="fbase", wait = "wbase"), quote = TRUE)


   # 7. DESIGN WHEN THE MAIN TRAVEL MODE FOR THE OPT-OUT ALTERNATIVE IS: FEET
```

```
ced7 <- Lma.design (candidate.array = NULL,
   attribute.names = list (mode = c("bike", "bshar", "car", "cshar", "taxi",
        "transit"),
        cost = c("COSTOlow", "COSTObase", "COSTOhigh"),
        time = c("TEMPOlow", "TEMPObase", "TEMPOhigh"),
        feet = c("MARCIAlow", "MARCIAbase", "MARCIAhigh"),
        wait = c("ATTESAlow", "ATTESAbase", "ATTESAhigh")),
   nalternatives = 1,
   nblocks = 3,
   row.renames = TRUE,
   seed = 123)
quest_feet <- questionnaire (ced7, quote = TRUE)
```

Factorial design

The output of the previously reported script is shown below.

DESIGN WHEN THE MAIN TRAVEL MODE FOR THE OPT-OUT ALTERNATIVE IS: **CAR**

Question 1	Block 1	Block 2	Block 3
mode	cshar	bshar	taxi
cost	COSTOlow	COSTOlow	COSTOlow
time	TEMPOlow	TEMPOhigh	TEMPObase
feet	MARCIAlow	MARCIAbase	MARCIAlow
wait	ATTESAlow	ATTESAhigh	ATTESAhigh
Question 2	Block 1	Block 2	Block 3
mode	bike	bike	car
cost	COSTObase	COSTOhigh	COSTOhigh
time	TEMPObase	TEMPOhigh	TEMPObase
feet	MARCIAhigh	MARCIAlow	MARCIAbase
wait	ATTESAhigh	ATTESAlow	ATTESAlow
Question 3	Block 1	Block 2	Block 3
mode	car	transit	bike
cost	COSTOlow	COSTOlow	COSTOlow
time	TEMPOhigh	TEMPObase	TEMPOlow
feet	MARCIAhigh	MARCIAhigh	MARCIAbase
wait	ATTESAbase	ATTESAlow	ATTESAbase
Question 4	Block 1	Block 2	Block 3
mode	bshar	car	cshar
cost	COSTOhigh	COSTObase	COSTOhigh
time	TEMPObase	TEMPOlow	TEMPOhigh
feet	MARCIAlow	MARCIAlow	MARCIAhigh
wait	ATTESAbase	ATTESAhigh	ATTESAhigh
Question 5	Block 1	Block 2	Block 3

DESIGN WHEN THE MAIN TRAVEL MODE FOR THE OPT-OUT ALTERNATIVE IS: **CAR SHARING**

Question 1	Block 1	Block 2	Block 3
mode	bshar	car	bike
cost	COSTOhigh	COSTObase	COSTOlow
time	TEMPObase	TEMPObase	TEMPOlow
feet	MARCIAlow	MARCIAbase	MARCIAbase
wait	ATTESAbase	ATTESAbase	ATTESAbase
Question 2	Block 1	Block 2	Block 3
mode	cshar	transit	taxi
cost	COSTOlow	COSTOlow	COSTOlow
time	TEMPOhigh	TEMPObase	TEMPObase
feet	MARCIAhigh	MARCIAhigh	MARCIAlow
wait	ATTESAbase	ATTESAlow	ATTESAhigh
Question 3	Block 1	Block 2	Block 3
mode	transit	cshar	transit
cost	COSTOhigh	COSTObase	COSTObase
time	TEMPOlow	TEMPOlow	TEMPOhigh
feet	MARCIAbase	MARCIAlow	MARCIAlow
wait	ATTESAhigh	ATTESAhigh	ATTESAbase
Question 4	Block 1	Block 2	Block 3
mode	bike	taxi	car
cost	COSTObase	COSTOhigh	COSTOhigh
time	TEMPObase	TEMPOlow	TEMPOhigh
feet	MARCIAhigh	MARCIAhigh	MARCIAhigh
wait	ATTESAhigh	ATTESAbase	ATTESAhigh
Question 5	Block 1	Block 2	Block 3

mode	transit	taxi	transit		**mode**	taxi	bshar	cshar
cost	COSTOhigh	COSTOhigh	COSTObase		**cost**	COSTObase	COSTOlow	COSTOhigh
time	TEMPOlow	TEMPOlow	TEMPOhigh		**time**	TEMPOhigh	TEMPOhigh	TEMPObase
feet	MARCIAbase	MARCIAhigh	MARCIAlow		**feet**	MARCIAbase	MARCIAbase	MARCIAbase
wait	ATTESAhigh	ATTESAbase	ATTESAbase		**wait**	ATTESAlow	ATTESAhigh	ATTESAlow
Question 6	Block 1	Block 2	Block 3		**Question 6**	Block 1	Block 2	Block 3
mode	taxi	cshar	bshar		**mode**	car	bike	bshar
cost	COSTObase	COSTObase	COSTObase		**cost**	COSTOlow	COSTOhigh	COSTObase
time	TEMPOhigh	TEMPObase	TEMPOlow		**time**	TEMPOlow	TEMPOhigh	TEMPOlow
feet	MARCIAbase	MARCIAbase	MARCIAhigh		**feet**	MARCIAlow	MARCIAlow	MARCIAhigh
wait	ATTESAlow	ATTESAbase	ATTESAlow		**wait**	ATTESAlow	ATTESAlow	ATTESAlow

DESIGN WHEN THE MAIN TRAVEL MODE
FOR THE OPT-OUT ALTERNATIVE IS: **TAXI**

Question 1	Block 1	Block 2	Block 3
mode	transit	car	cshar
cost	COSTOlow	COSTOhigh	COSTOlow
time	TEMPOlow	TEMPOhigh	TEMPObase
feet	MARCIAlow	MARCIAlow	MARCIAlow
wait	ATTESAlow	ATTESAlow	ATTESAhigh
Question 2	Block 1	Block 2	Block 3
mode	bshar	bshar	bike
cost	COSTOhigh	COSTOlow	COSTObase
time	TEMPObase	TEMPOhigh	TEMPOhigh
feet	MARCIAlow	MARCIAbase	MARCIAlow
wait	ATTESAbase	ATTESAhigh	ATTESAbase
Question 3	Block 1	Block 2	Block 3
mode	taxi	taxi	taxi
cost	COSTOlow	COSTObase	COSTOhigh
time	TEMPOhigh	TEMPOlow	TEMPObase
feet	MARCIAhigh	MARCIAlow	MARCIAbase
wait	ATTESAbase	ATTESAhigh	ATTESAlow
Question 4	Block 1	Block 2	Block 3
mode	cshar	transit	car
cost	COSTObase	COSTObase	COSTOlow
time	TEMPOhigh	TEMPObase	TEMPOlow
feet	MARCIAbase	MARCIAbase	MARCIAbase
wait	ATTESAlow	ATTESAbase	ATTESAbase
Question 5	Block 1	Block 2	Block 3
mode	bike	bike	bshar

DESIGN WHEN THE MAIN TRAVEL MODE
FOR THE OPT-OUT ALTERNATIVE IS: **TRANSIT**

Question 1	Block 1	Block 2	Block 3
mode	taxi	bshar	taxi
cost	COSTOlow	COSTOlow	COSTOhigh
time	TEMPOlow	TEMPOhigh	TEMPOhigh
feet	MARCIAlow	MARCIAbase	MARCIAhigh
wait	ATTESAlow	ATTESAhigh	ATTESAhigh
Question 2	Block 1	Block 2	Block 3
mode	bshar	taxi	cshar
cost	COSTOhigh	COSTObase	COSTOlow
time	TEMPObase	TEMPObase	TEMPObase
feet	MARCIAlow	MARCIAbase	MARCIAlow
wait	ATTESAbase	ATTESAbase	ATTESAhigh
Question 3	Block 1	Block 2	Block 3
mode	transit	car	car
cost	COSTOlow	COSTOhigh	COSTOlow
time	TEMPOhigh	TEMPOhigh	TEMPOlow
feet	MARCIAhigh	MARCIAlow	MARCIAbase
wait	ATTESAbase	ATTESAlow	ATTESAbase
Question 4	Block 1	Block 2	Block 3
mode	car	bike	bshar
cost	COSTObase	COSTOlow	COSTObase
time	TEMPObase	TEMPObase	TEMPOlow
feet	MARCIAhigh	MARCIAhigh	MARCIAhigh
wait	ATTESAhigh	ATTESAlow	ATTESAlow
Question 5	Block 1	Block 2	Block 3
mode	cshar	transit	bike

cost	COSTOhigh	COSTOlow	COSTObase
time	TEMPOlow	TEMPObase	TEMPOlow
feet	MARCIAbase	MARCIAhigh	MARCIAhigh
wait	ATTESAhigh	ATTESAlow	ATTESAlow
Question 6	Block 1	Block 2	Block 3
mode	car	cshar	transit
cost	COSTObase	COSTOhigh	COSTOhigh
time	TEMPObase	TEMPOlow	TEMPOhigh
feet	MARCIAhigh	MARCIAhigh	MARCIAhigh
wait	ATTESAhigh	ATTESAbase	ATTESAhigh

cost	COSTObase	COSTObase	COSTObase
time	TEMPOhigh	TEMPOlow	TEMPOhigh
feet	MARCIAbase	MARCIAlow	MARCIAlow
wait	ATTESAlow	ATTESAhigh	ATTESAbase
Question 6	Block 1	Block 2	Block 3
mode	bike	cshar	transit
cost	COSTOhigh	COSTOhigh	COSTOhigh
time	TEMPOlow	TEMPOlow	TEMPObase
feet	MARCIAbase	MARCIAhigh	MARCIAbase
wait	ATTESAhigh	ATTESAbase	ATTESAlow

DESIGN WHEN THE MAIN TRAVEL MODE
FOR THE OPT-OUT ALTERNATIVE IS: **BIKE**

Question 1	Block 1	Block 2	Block 3
mode	transit	transit	car
cost	COSTOhigh	COSTOlow	COSTOlow
time	TEMPObase	TEMPOhigh	TEMPOlow
feet	MARCIAlow	MARCIAbase	MARCIAbase
wait	ATTESAbase	ATTESAhigh	ATTESAbase
Question 2	Block 1	Block 2	Block 3
mode	bshar	cshar	cshar
cost	COSTOlow	COSTOhigh	COSTOlow
time	TEMPOlow	TEMPOlow	TEMPObase
feet	MARCIAlow	MARCIAhigh	MARCIAlow
wait	ATTESAlow	ATTESAbase	ATTESAhigh
Question 3	Block 1	Block 2	Block 3
mode	car	bike	transit
cost	COSTObase	COSTObase	COSTObase
time	TEMPObase	TEMPOlow	TEMPOlow
feet	MARCIAhigh	MARCIAlow	MARCIAhigh
wait	ATTESAhigh	ATTESAhigh	ATTESAlow
Question 4	Block 1	Block 2	Block 3
mode	cshar	bshar	bike
cost	COSTObase	COSTObase	COSTOhigh
time	TEMPOhigh	TEMPObase	TEMPObase
feet	MARCIAbase	MARCIAbase	MARCIAbase
wait	ATTESAlow	ATTESAbase	ATTESAlow
Question 5	Block 1	Block 2	Block 3
mode	bike	taxi	taxi
cost	COSTOlow	COSTOlow	COSTObase

DESIGN WHEN THE MAIN TRAVEL MODE
FOR THE OPT-OUT ALTERNATIVE IS: **BIKE SHARING**

Question 1	Block 1	Block 2	Block 3
mode	bike	taxi	taxi
cost	COSTOlow	COSTOlow	COSTObase
time	TEMPOlow	TEMPObase	TEMPOhigh
feet	MARCIAlow	MARCIAhigh	MARCIAlow
wait	ATTESAlow	ATTESAlow	ATTESAbase
Question 2	Block 1	Block 2	Block 3
mode	taxi	cshar	transit
cost	COSTOhigh	COSTOhigh	COSTObase
time	TEMPOlow	TEMPOlow	TEMPOlow
feet	MARCIAbase	MARCIAhigh	MARCIAhigh
wait	ATTESAhigh	ATTESAbase	ATTESAlow
Question 3	Block 1	Block 2	Block 3
mode	bshar	bike	car
cost	COSTOlow	COSTObase	COSTOlow
time	TEMPOhigh	TEMPObase	TEMPOlow
feet	MARCIAhigh	MARCIAbase	MARCIAbase
wait	ATTESAbase	ATTESAbase	ATTESAbase
Question 4	Block 1	Block 2	Block 3
mode	car	transit	cshar
cost	COSTObase	COSTOlow	COSTOlow
time	TEMPObase	TEMPOhigh	TEMPObase
feet	MARCIAhigh	MARCIAbase	MARCIAlow
wait	ATTESAhigh	ATTESAhigh	ATTESAhigh
Question 5	Block 1	Block 2	Block 3
mode	cshar	bshar	bike
cost	COSTObase	COSTObase	COSTOhigh

time	TEMPOhigh	TEMPObase	TEMPOhigh
feet	MARCIAhigh	MARCIAhigh	MARCIAlow
wait	ATTESAbase	ATTESAlow	ATTESAbase
Question 6	Block 1	Block 2	Block 3
mode	taxi	car	bshar
cost	COSTOhigh	COSTOhigh	COSTOhigh
time	TEMPOlow	TEMPOhigh	TEMPOhigh
feet	MARCIAbase	MARCIAlow	MARCIAhigh
wait	ATTESAhigh	ATTESAlow	ATTESAhigh

time	TEMPOhigh	TEMPOlow	TEMPOhigh
feet	MARCIAbase	MARCIAlow	MARCIAhigh
wait	ATTESAlow	ATTESAhigh	ATTESAhigh
Question 6	Block 1	Block 2	Block 3
mode	transit	car	bshar
cost	COSTOhigh	COSTOhigh	COSTOhigh
time	TEMPObase	TEMPOhigh	TEMPObase
feet	MARCIAlow	MARCIAlow	MARCIAbase
wait	ATTESAbase	ATTESAlow	ATTESAlow

DESIGN WHEN THE MAIN TRAVEL MODE
FOR THE OPT-OUT ALTERNATIVE IS: **FEET**

Question 1	Block 1	Block 2	Block 3
mode	bike	transit	bshar
cost	COSTOlow	COSTObase	COSTOlow
time	TEMPOlow	TEMPOlow	TEMPOlow
feet	MARCIAlow	MARCIAlow	MARCIAbase
wait	ATTESAlow	ATTESAhigh	ATTESAbase
Question 2	Block 1	Block 2	Block 3
mode	cshar	cshar	transit
cost	COSTOhigh	COSTOlow	COSTOhigh
time	TEMPOlow	TEMPObase	TEMPObase
feet	MARCIAbase	MARCIAhigh	MARCIAbase
wait	ATTESAhigh	ATTESAlow	ATTESAlow
Question 3	Block 1	Block 2	Block 3
mode	car	taxi	bike
cost	COSTObase	COSTOlow	COSTOhigh
time	TEMPOhigh	TEMPOhigh	TEMPOhigh
feet	MARCIAbase	MARCIAbase	MARCIAhigh
wait	ATTESAlow	ATTESAhigh	ATTESAhigh
Question 4	Block 1	Block 2	Block 3
mode	transit	bike	car
cost	COSTOlow	COSTObase	COSTOlow
time	TEMPOhigh	TEMPObase	TEMPObase
feet	MARCIAhigh	MARCIAbase	MARCIAlow
wait	ATTESAbase	ATTESAbase	ATTESAhigh
Question 5	Block 1	Block 2	Block 3
mode	bshar	car	cshar
cost	COSTObase	COSTOhigh	COSTObase
time	TEMPObase	TEMPOlow	TEMPOhigh

feet	MARCIAhigh	MARCIAhigh	MARCIAlow
wait	ATTESAhigh	ATTESAbase	ATTESAbase
Question 6	Block 1	Block 2	Block 3
mode	taxi	bshar	taxi
cost	COSTOhigh	COSTOhigh	COSTObase
time	TEMPObase	TEMPOhigh	TEMPOlow
feet	MARCIAlow	MARCIAlow	MARCIAhigh
wait	ATTESAbase	ATTESAlow	ATTESAlow

Appendix B. Structures of calibrated Decision Trees

In this appendix, the structures of the calibrated Decision Trees are reported. Each figure corresponding to one of the nine Decision Trees was divided into subfigures for the sake of readability. Leaves are surrounded by rectangles and they report the predicted travel alternative with the weighted number of items belonging to the predicted and discarded mode, respectively. As explained in Section 5.3.3, in order to identify the rules for which a travel alternative in a leaf was predicted, the path from the root node to that leaf has to be followed.

B.1 Switching model from all modes towards car sharing

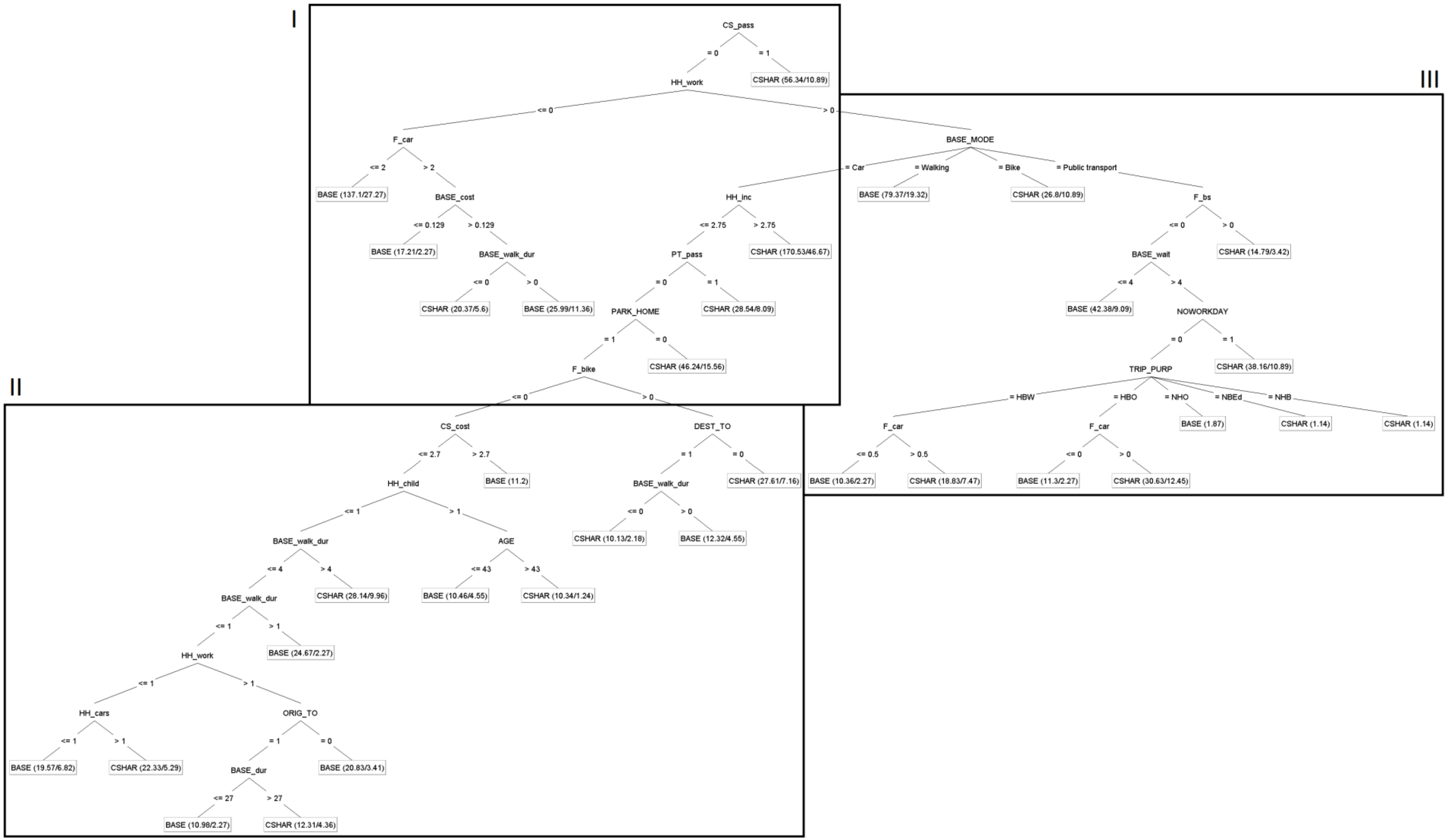


Figure 47. Decision tree for the switching towards car sharing (numbered subfigures are shown in the following)

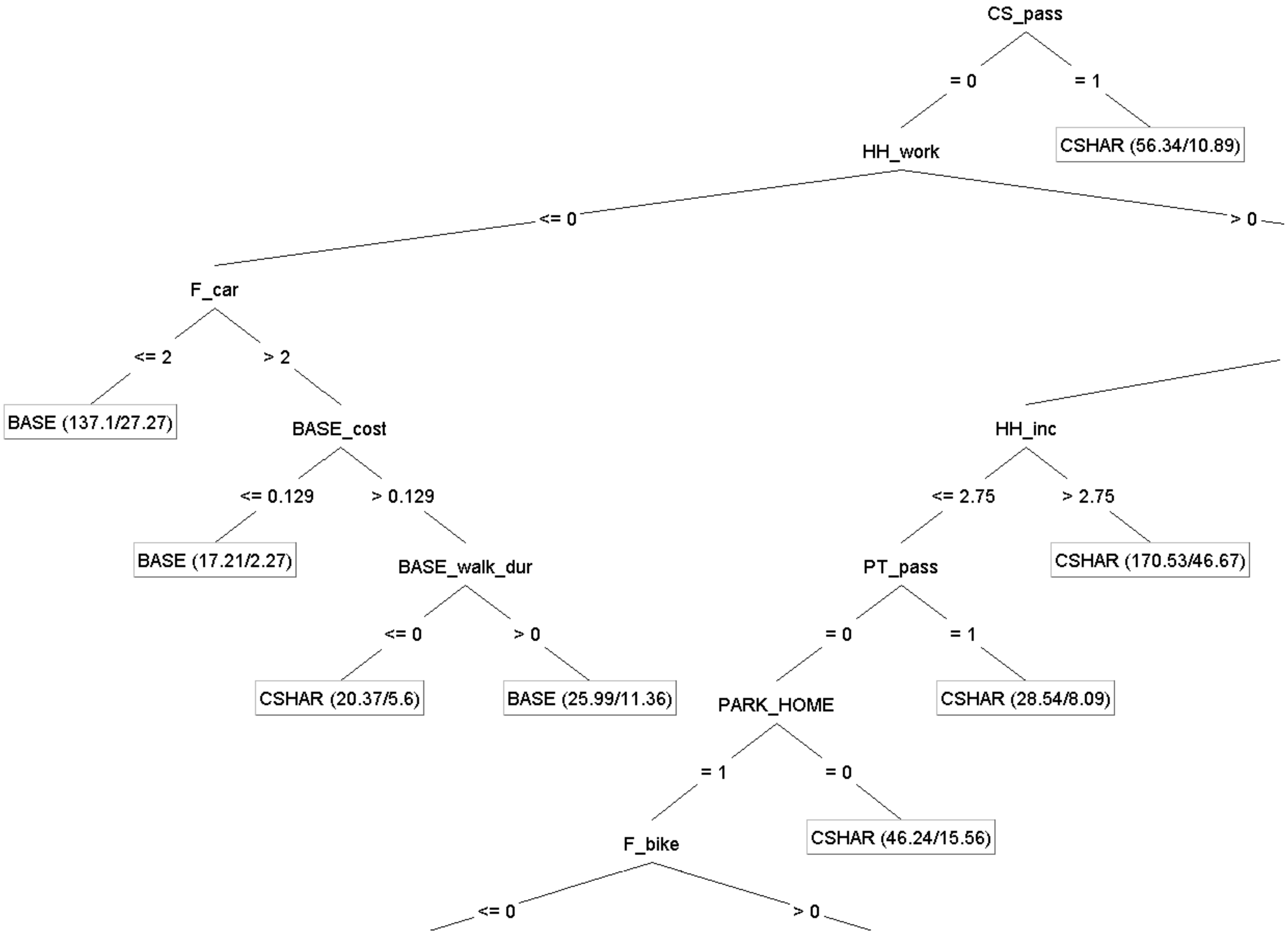


Figure 48. Subfigure I of the decision tree for the switching towards car sharing (Figure 47)

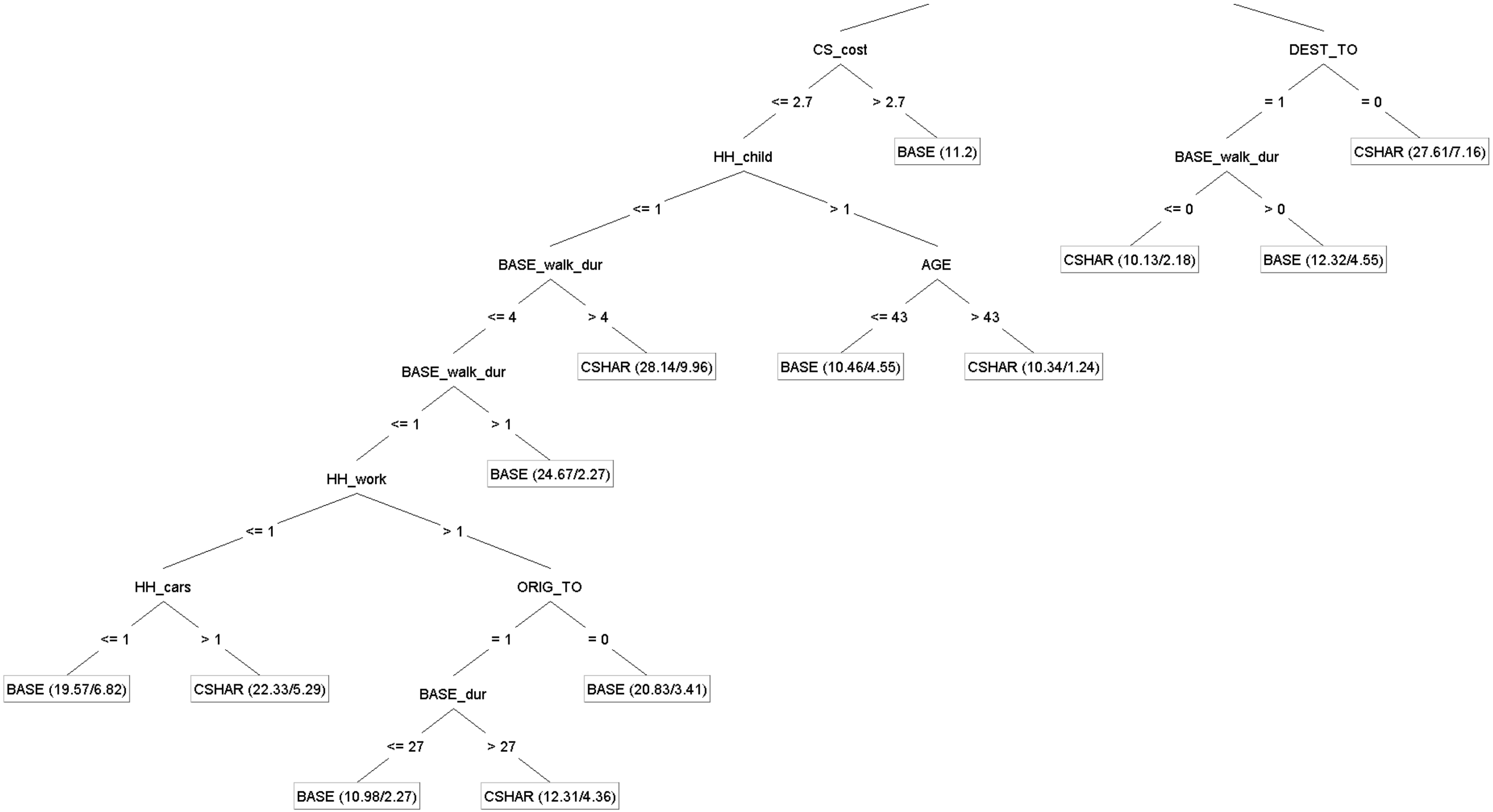


Figure 49. Subfigure II of the decision tree for the switching towards car sharing (Figure 47)

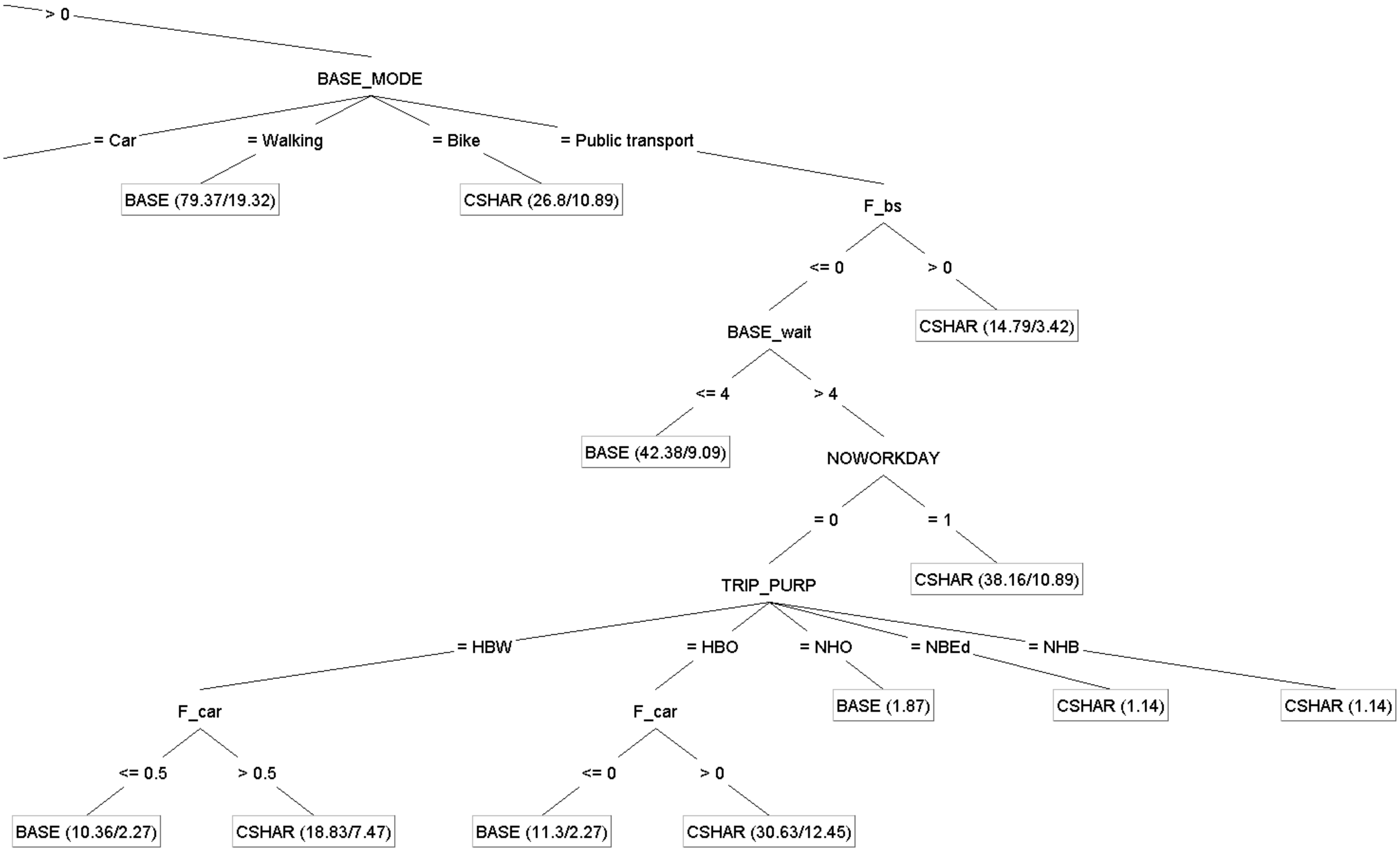


Figure 50. Subfigure III of the decision tree for the switching towards car sharing (Figure 47)

B.2 Switching model from private car towards car sharing

B.2.1 Absolute values of attributes of the alternative and the base mode

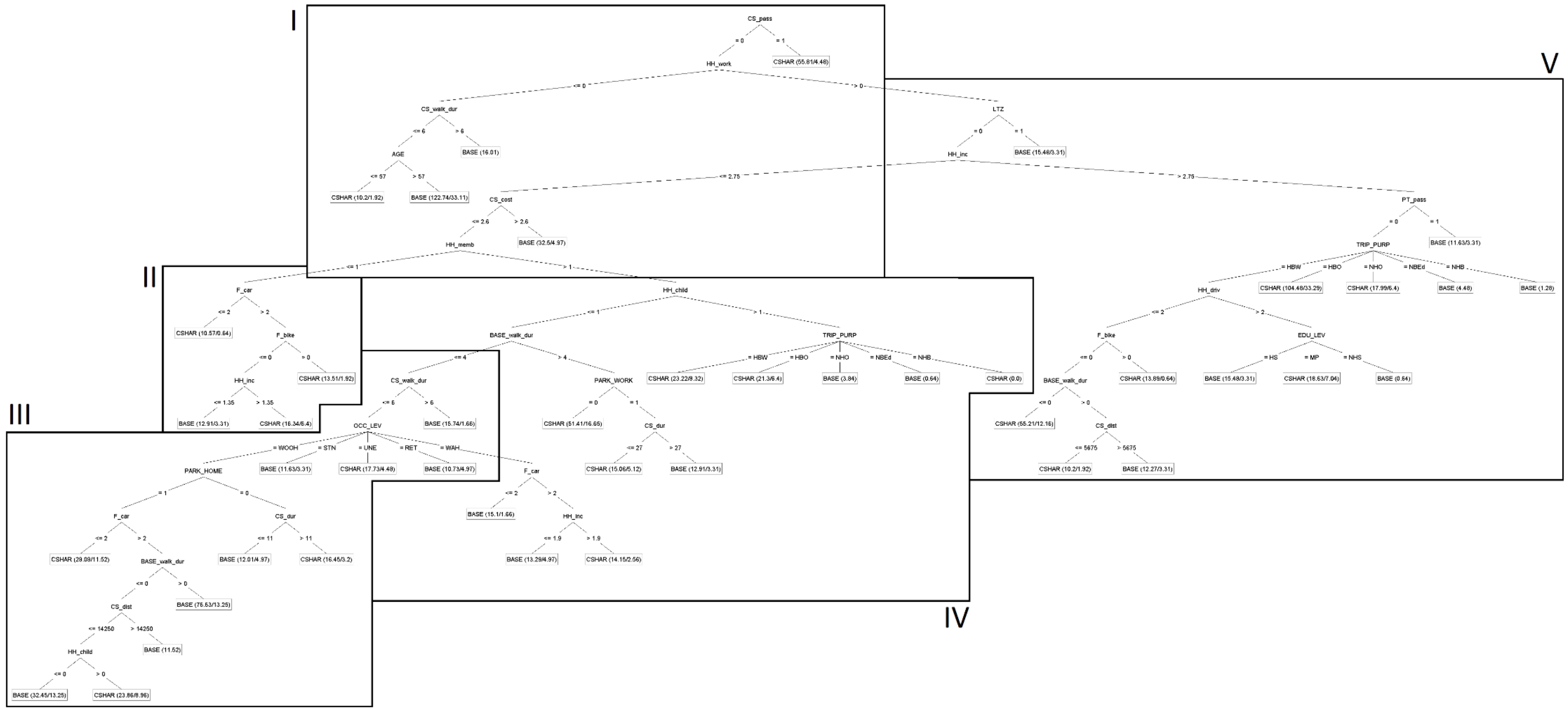


Figure 51. Decision tree for the switching intentions from car to car sharing (numbered subfigures are shown in the following)

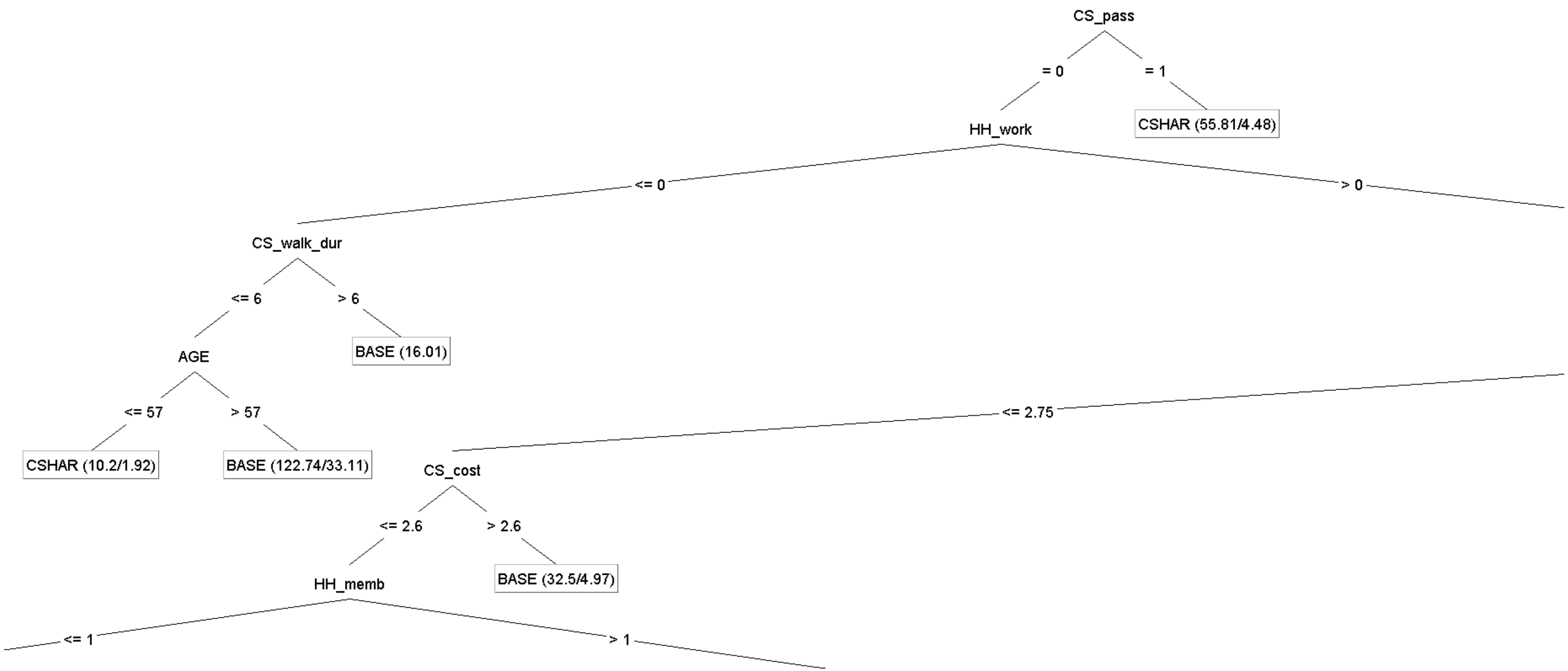


Figure 52. Subfigure I of the decision tree for the switching intentions from car to car sharing (Figure 51)

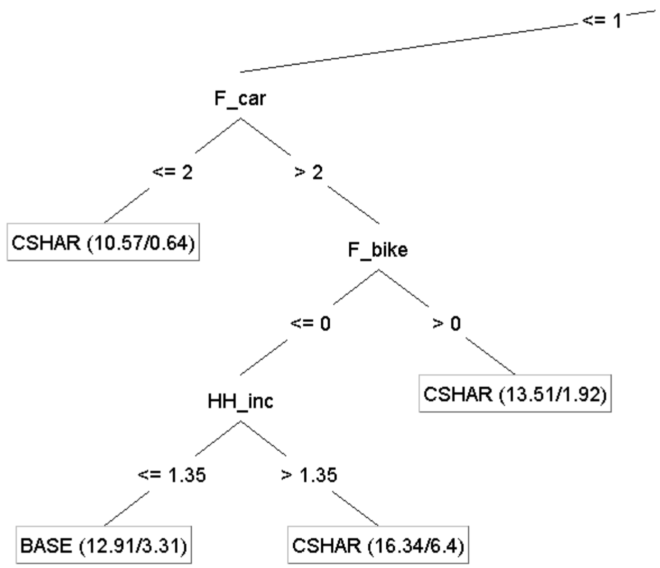


Figure 53. Subfigure II of the decision tree for the switching intentions from car to car sharing (Figure 51)

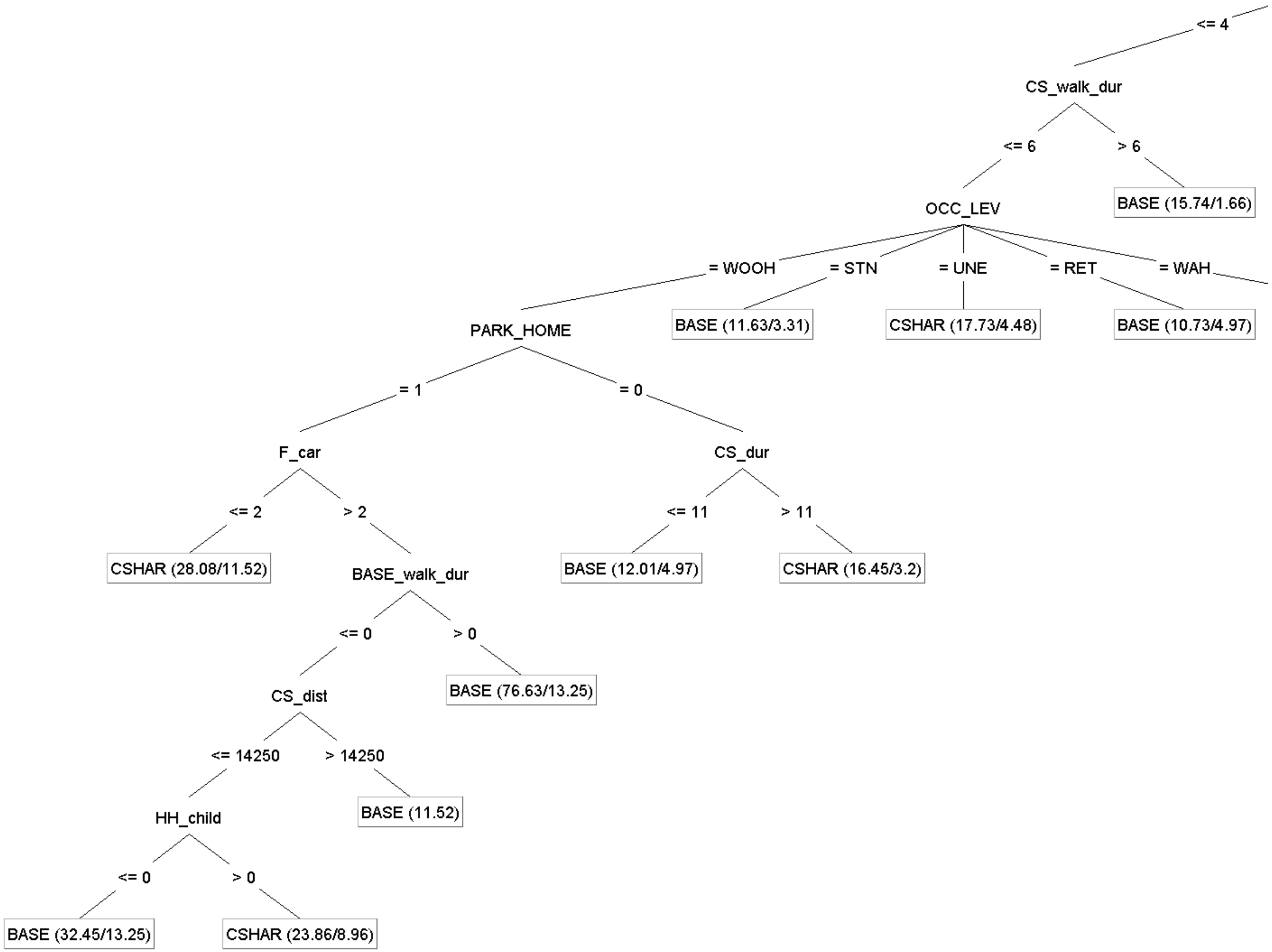


Figure 54. Subfigure III of the decision tree for the switching intentions from car to car sharing (Figure 51)

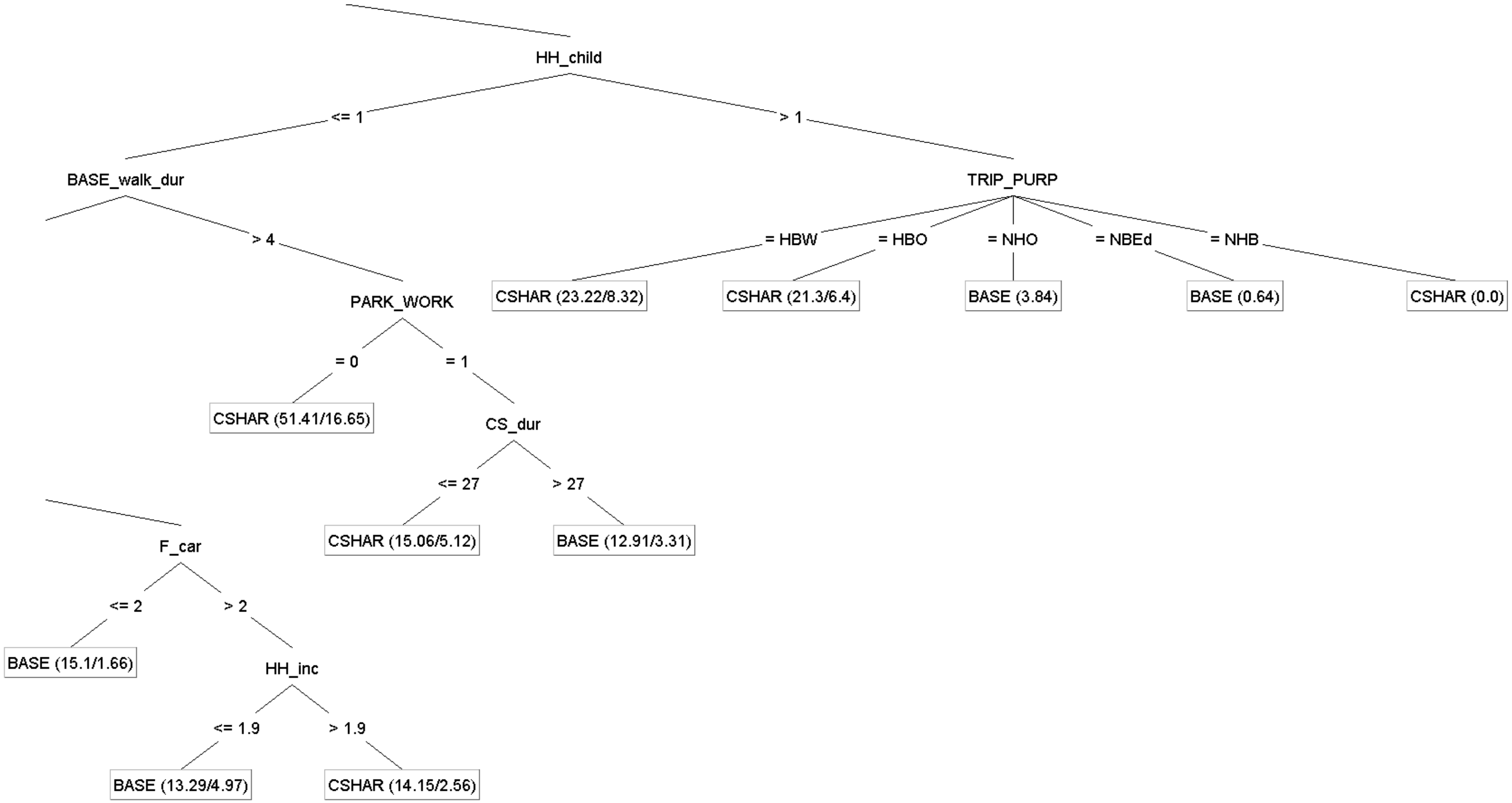


Figure 55. Subfigure IV of the decision tree for the switching intentions from car to car sharing (Figure 51)

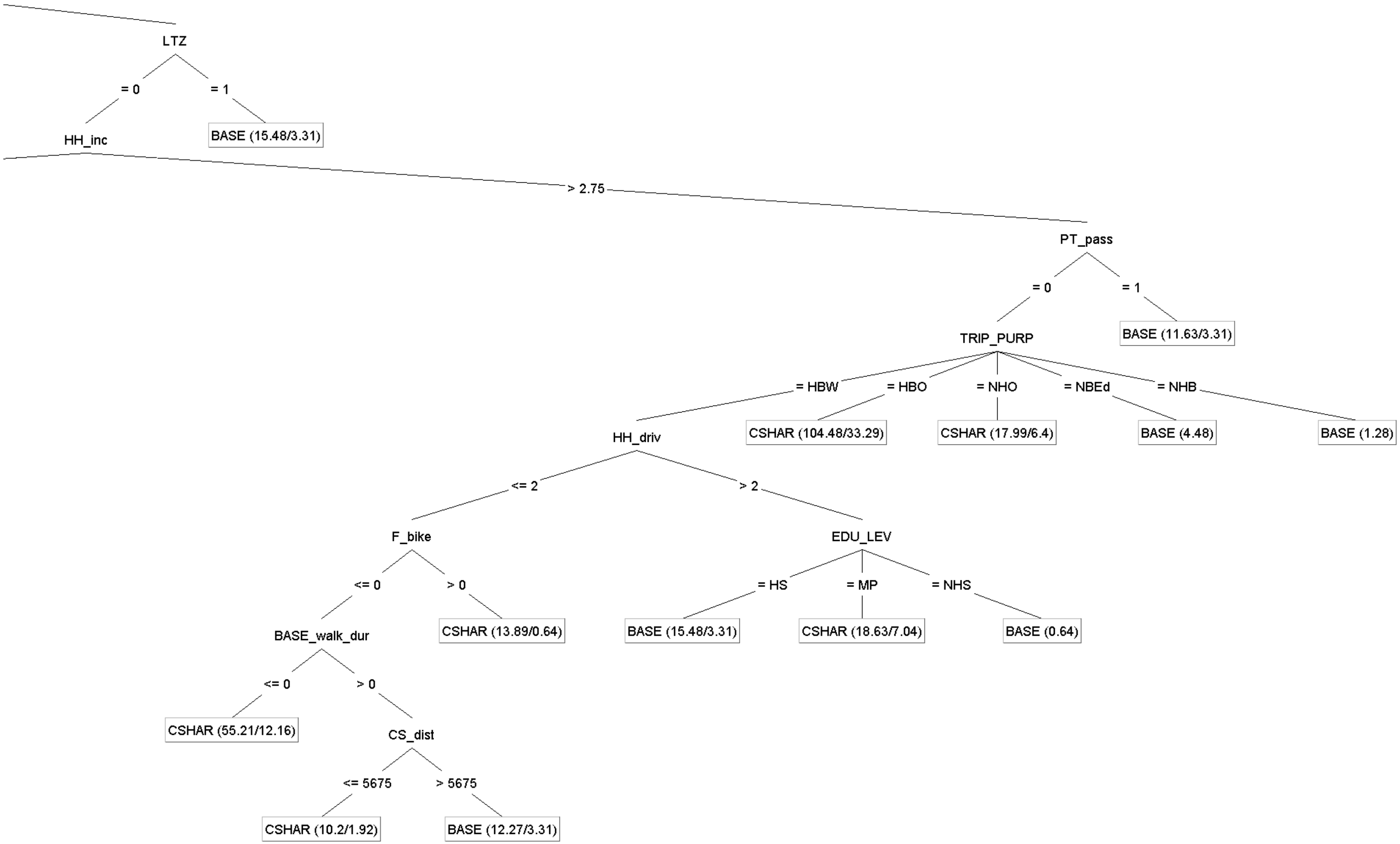


Figure 56. Subfigure IV of the decision tree for the switching intentions from car to car sharing (Figure 51)

B.2.2 Differences between attributes of the alternative and base mode

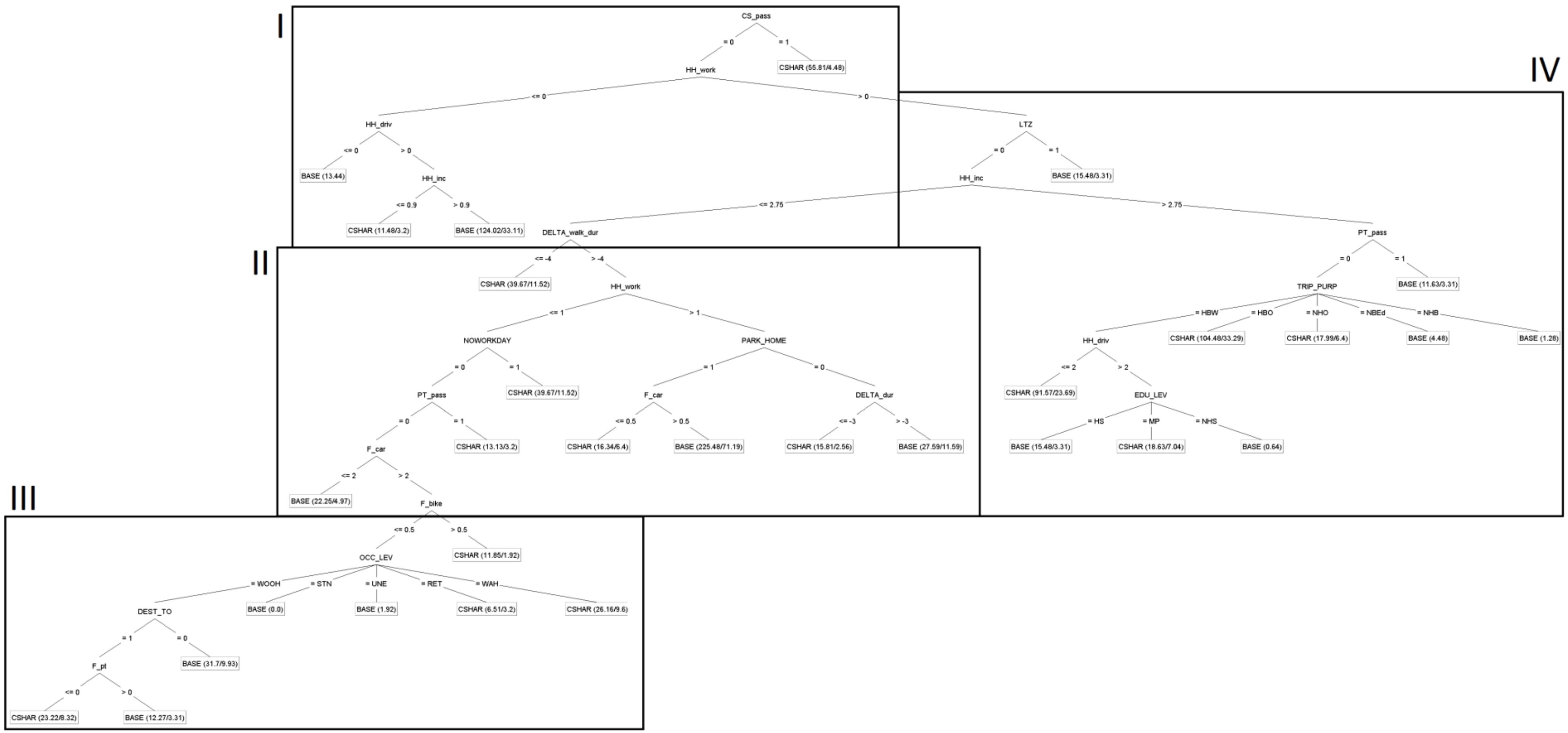


Figure 57. Decision tree for the switching intentions from car to car sharing (relative values of trip attributes) (numbered subfigures are shown in the following)

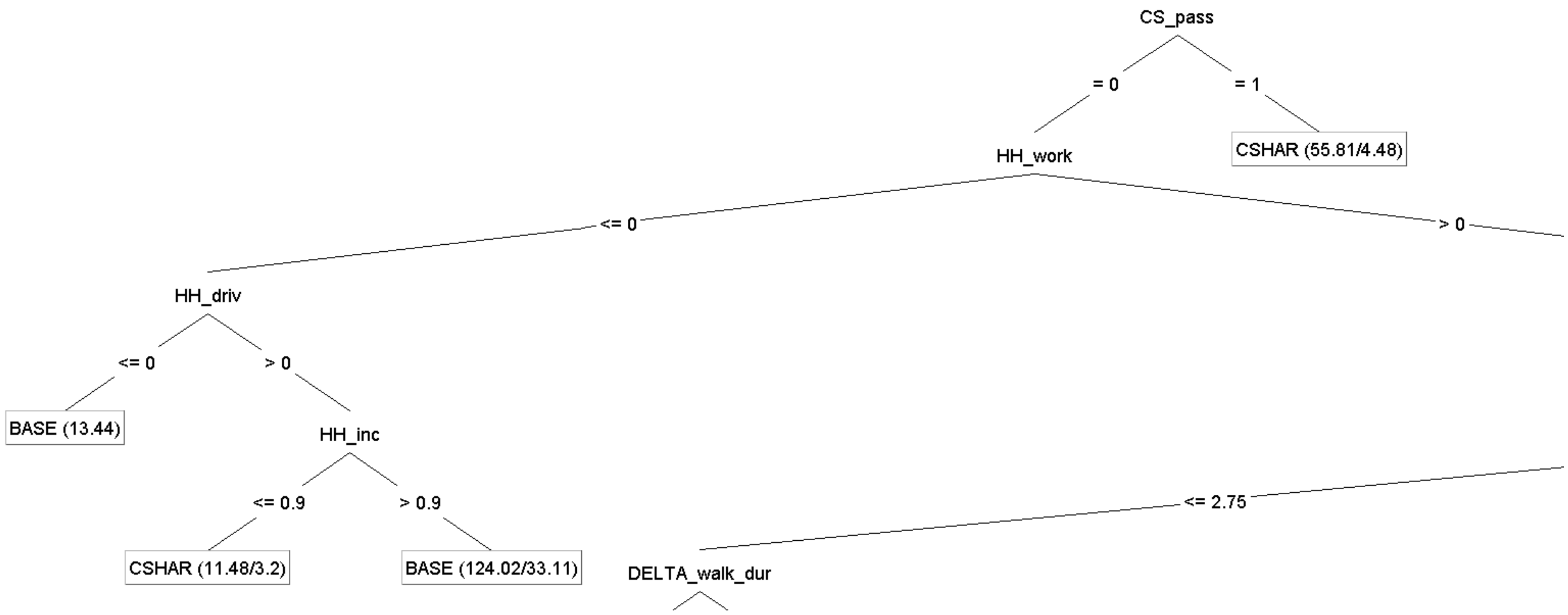


Figure 58. Subfigure I of the decision tree for the switching intentions from car to car sharing (relative values of trip attributes)

Figure 57)

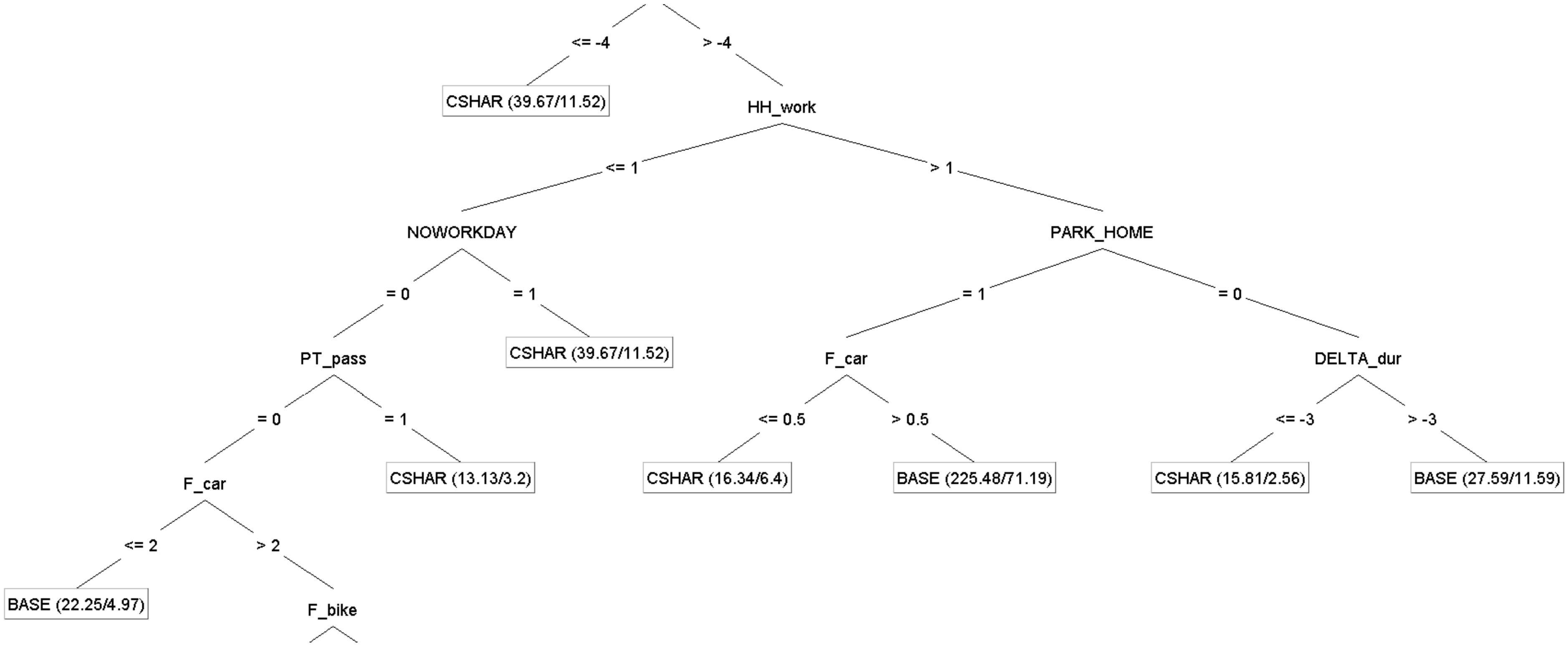


Figure 59. Subfigure II of the decision tree for the switching intentions from car to car sharing (relative values of trip attributes) (

Figure 57)

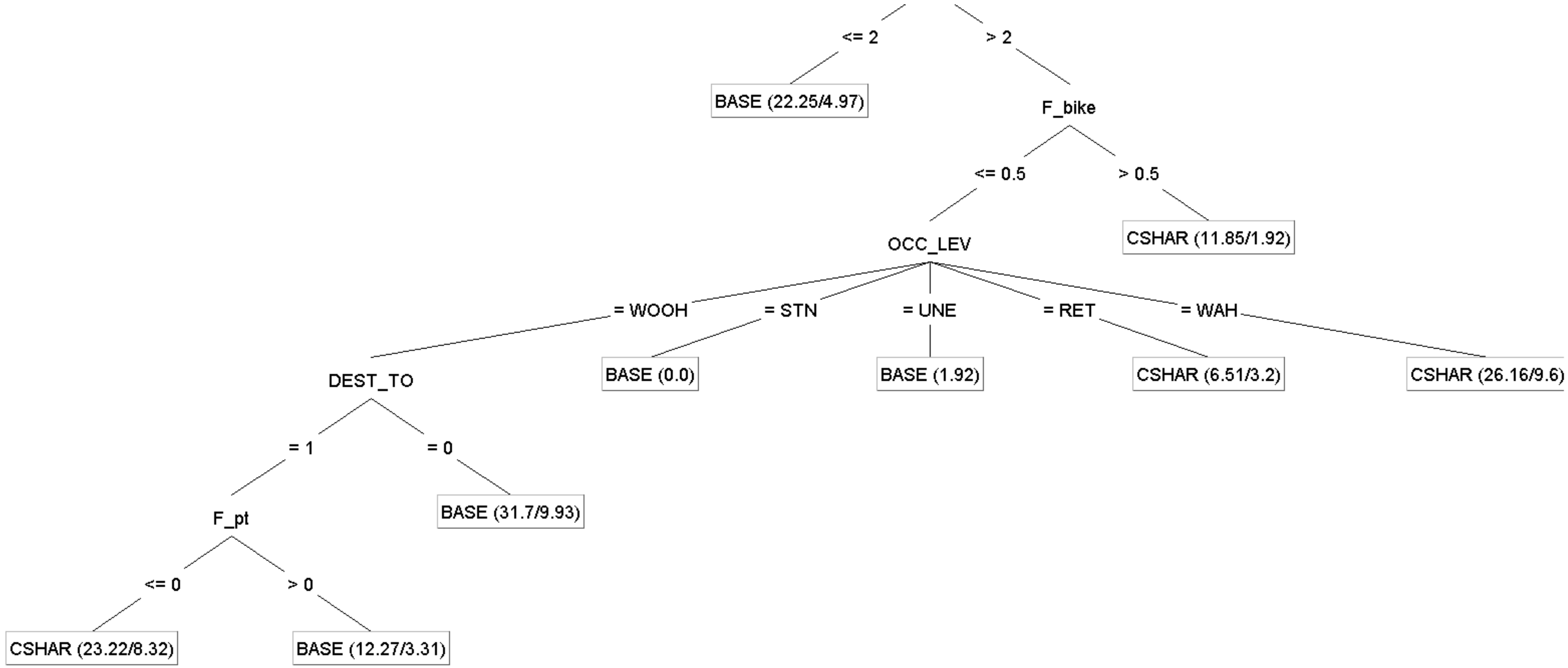


Figure 60. Subfigure III of the decision tree for the switching intentions from car to car sharing (relative values of trip attributes) (

Figure 57)

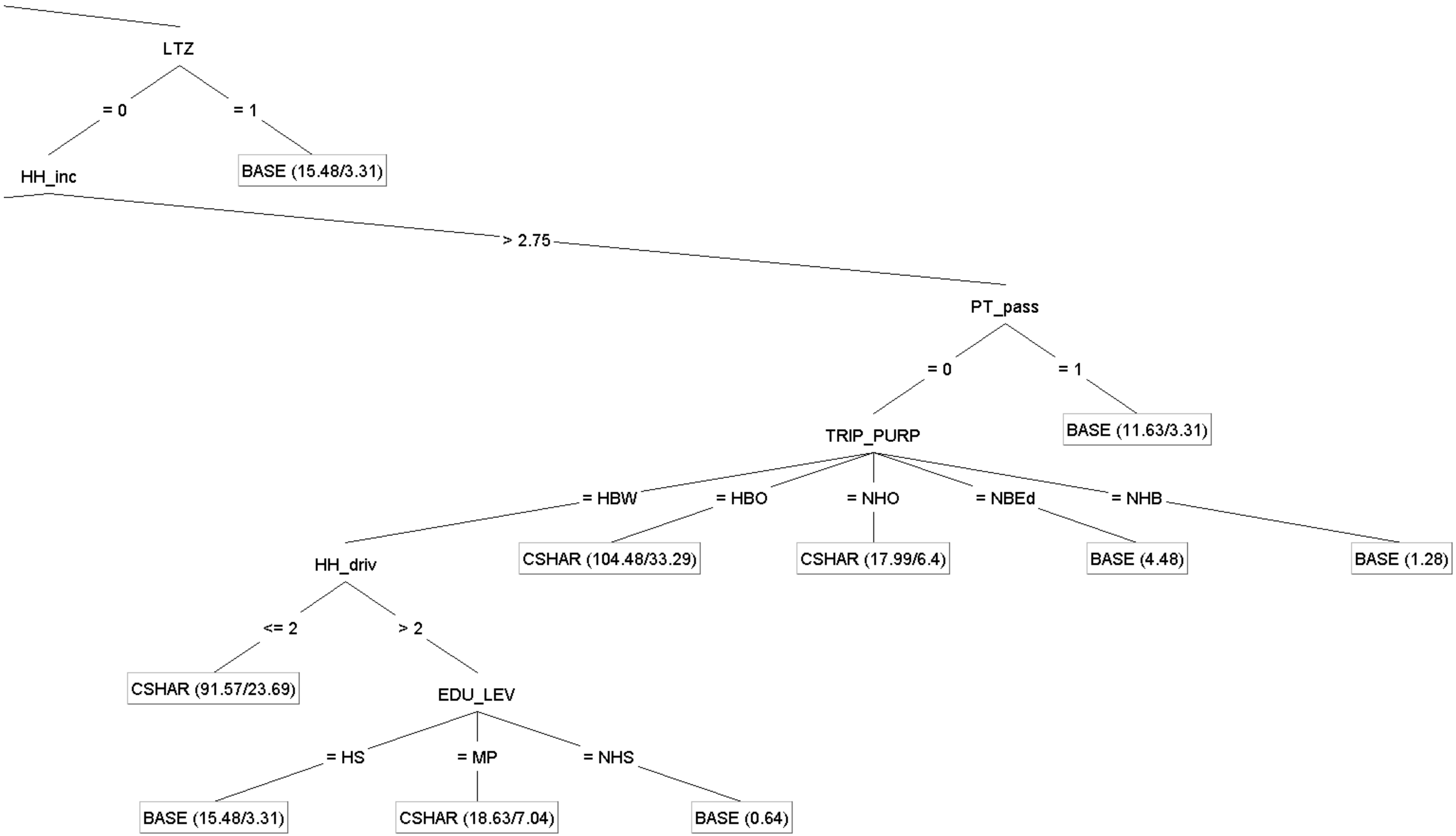


Figure 61. Subfigure IV of the decision tree for the switching intentions from car to car sharing (relative values of trip attributes) (

Figure 57)

B.3 Switching model from public transport towards car sharing

B.3.1 Absolute values of attributes of the alternative and the base mode

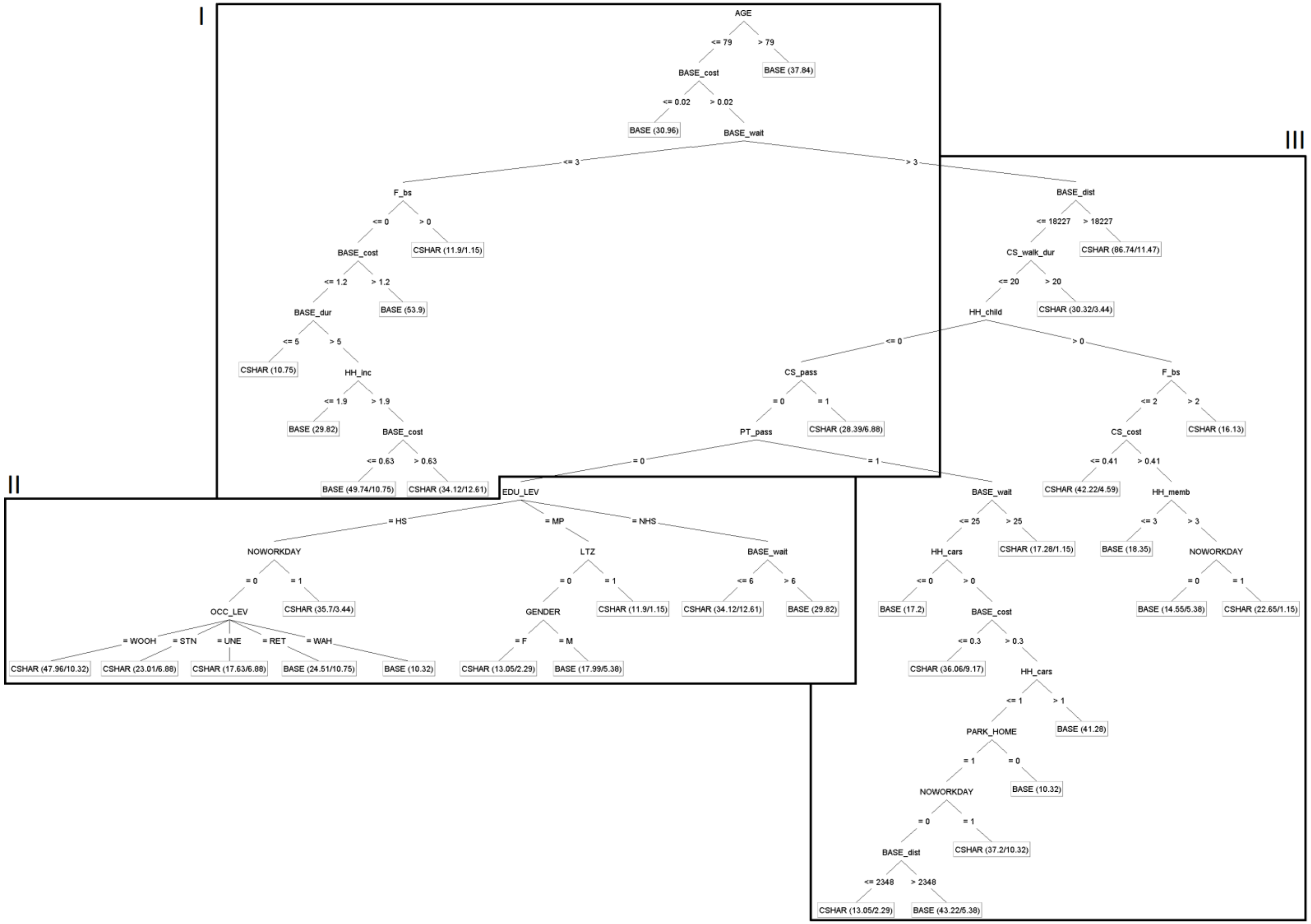


Figure 62. Decision tree for the switching intentions from public transport to car sharing (numbered subfigures are shown in the following)

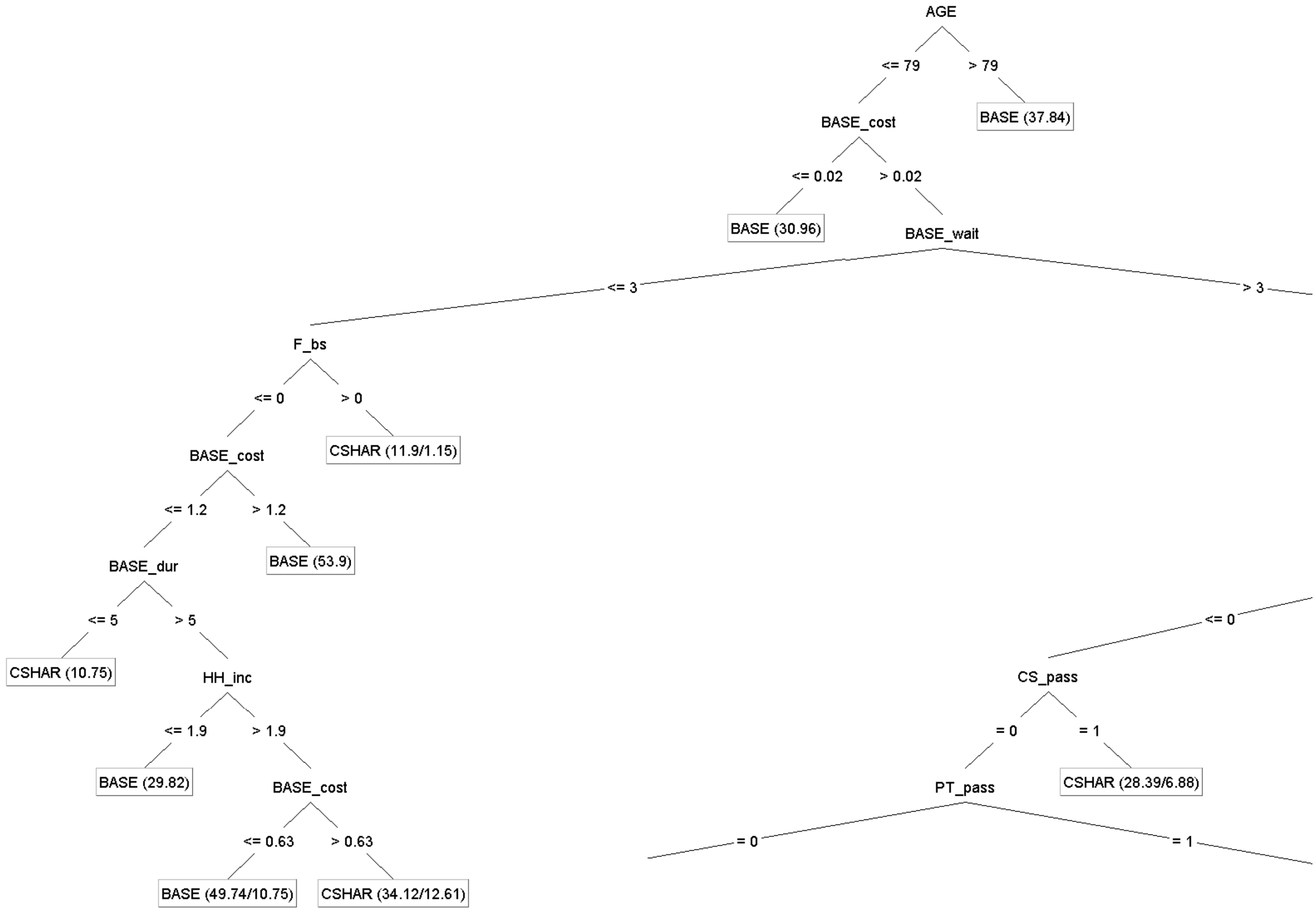


Figure 63. Subfigure I of the decision tree for the switching intentions from public transport to car sharing (Figure 62)

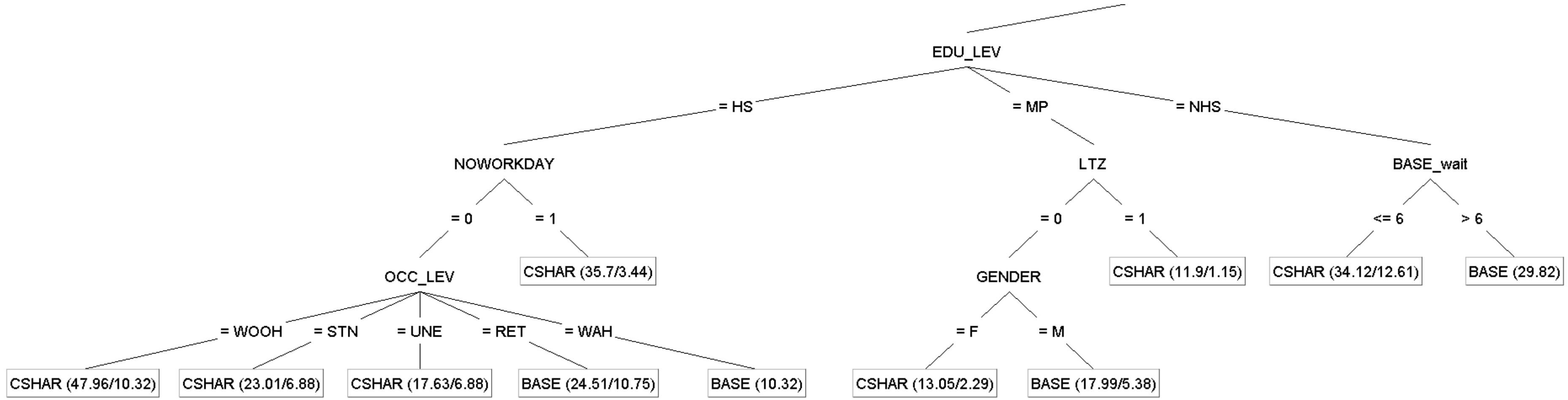


Figure 64. Subfigure II of the decision tree for the switching intentions from public transport to car sharing (Figure 62)

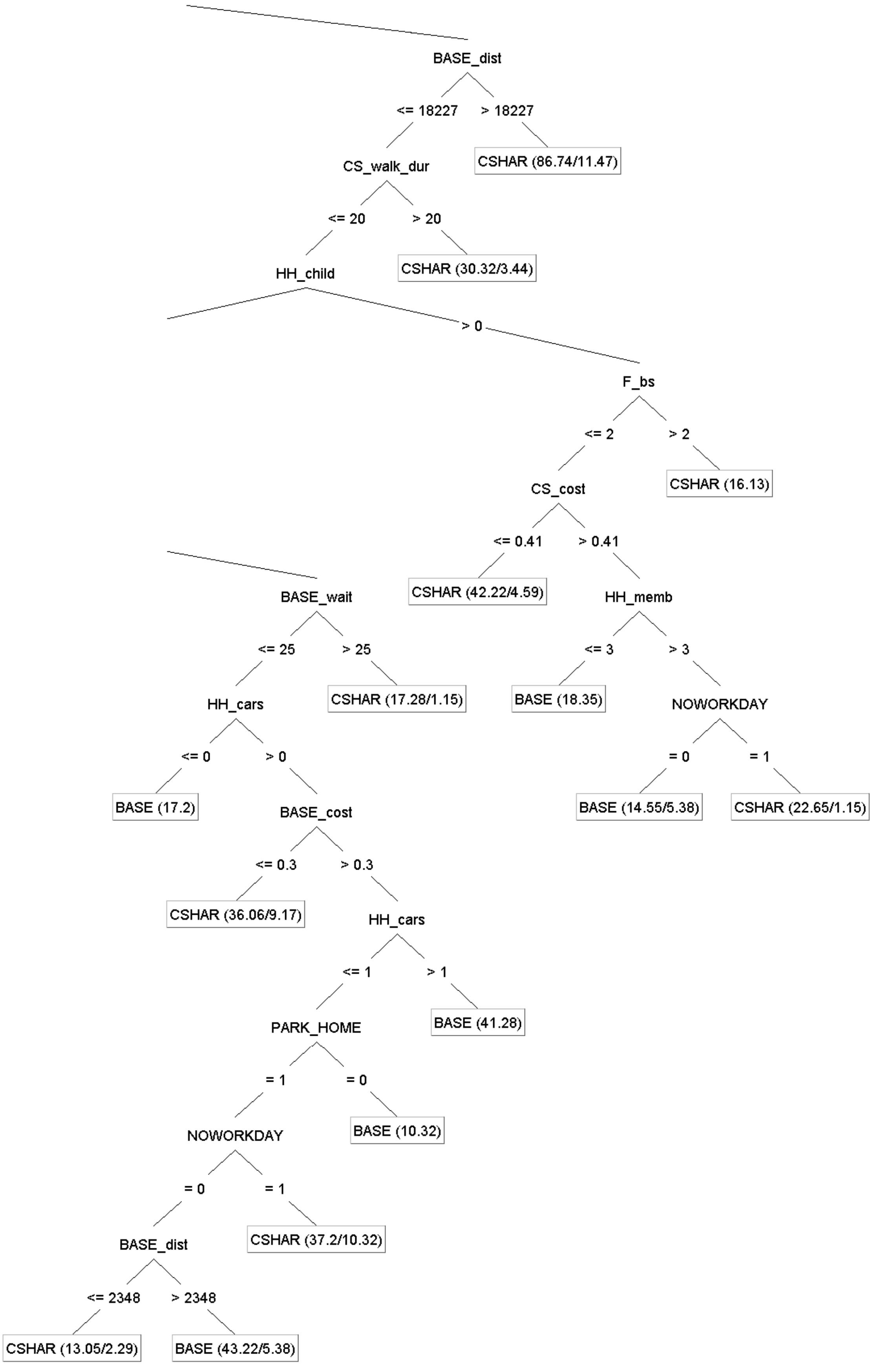


Figure 65. Subfigure III of the decision tree for the switching intentions from public transport to car sharing (Figure 62)

B.3.2 Differences between attributes of the alternative and base mode

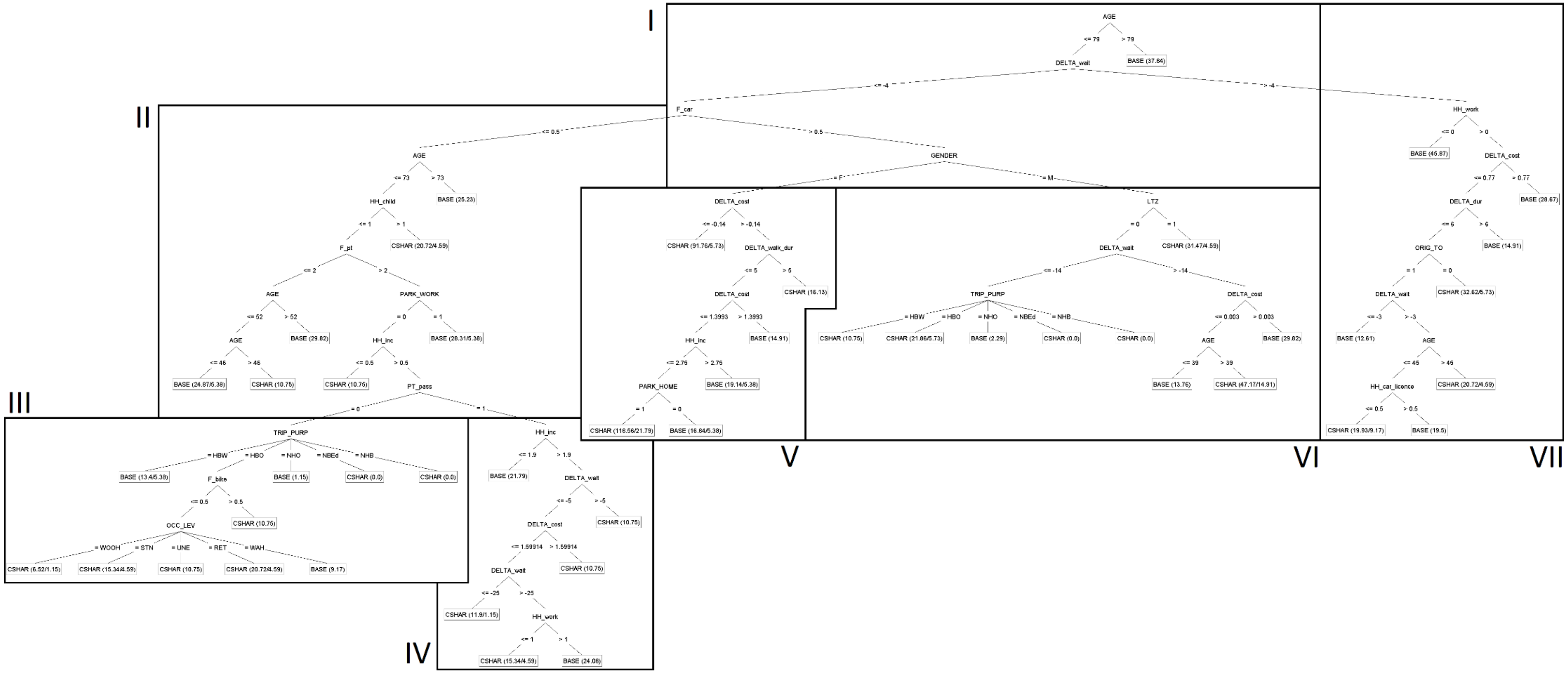


Figure 66. Decision tree for the switching intentions from public transport to car sharing (relative values of trip attributes) (numbered subfigures are shown in the following)

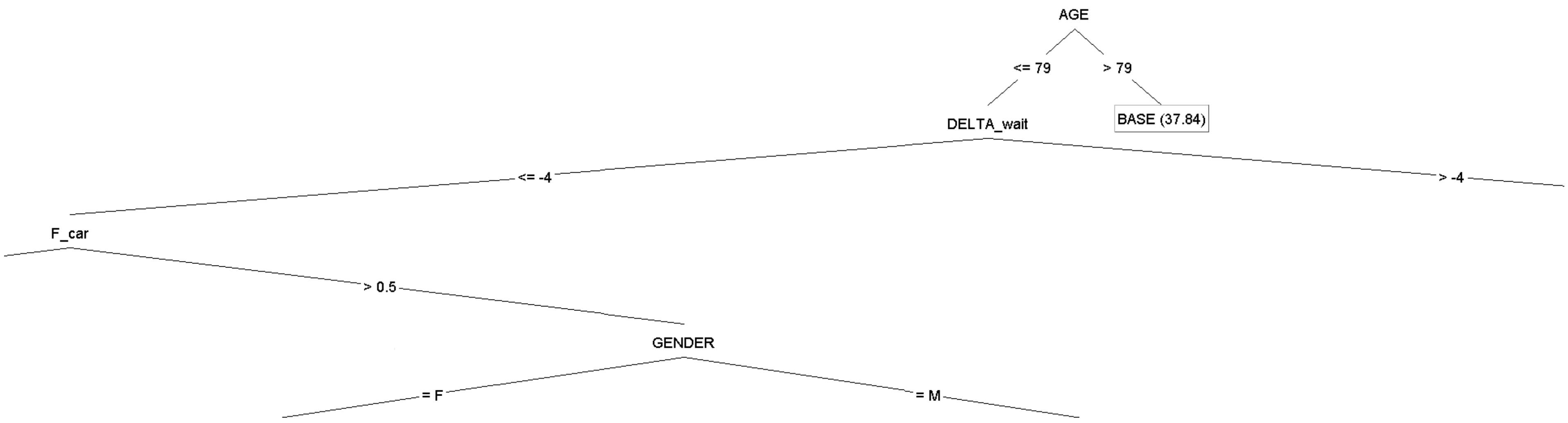


Figure 67. Subfigure I of the decision tree for the switching intentions from public transport to car sharing (relative values of trip attributes) (Figure 66)

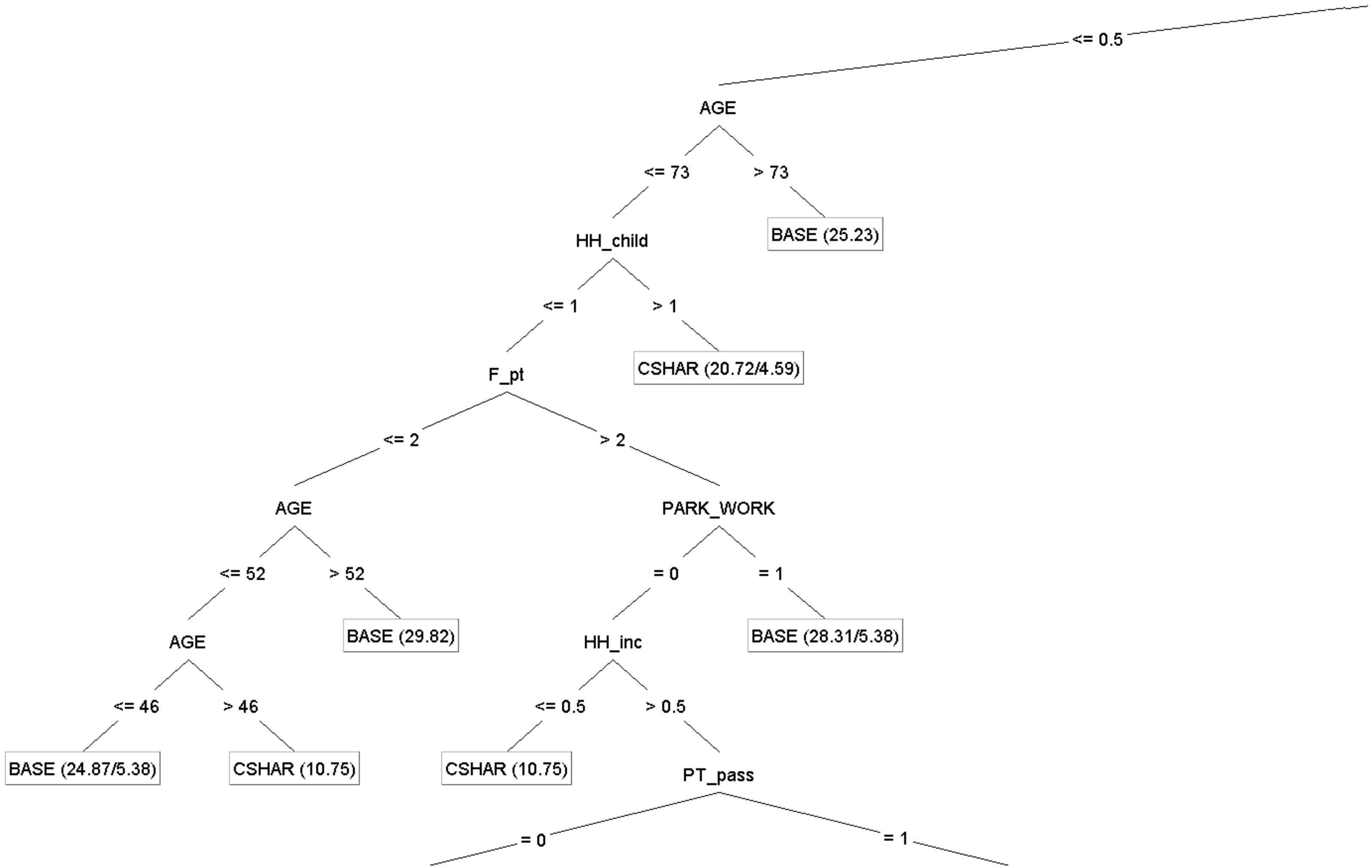


Figure 68. Subfigure II of the decision tree for the switching intentions from public transport to car sharing (relative values of trip attributes) (Figure 66)

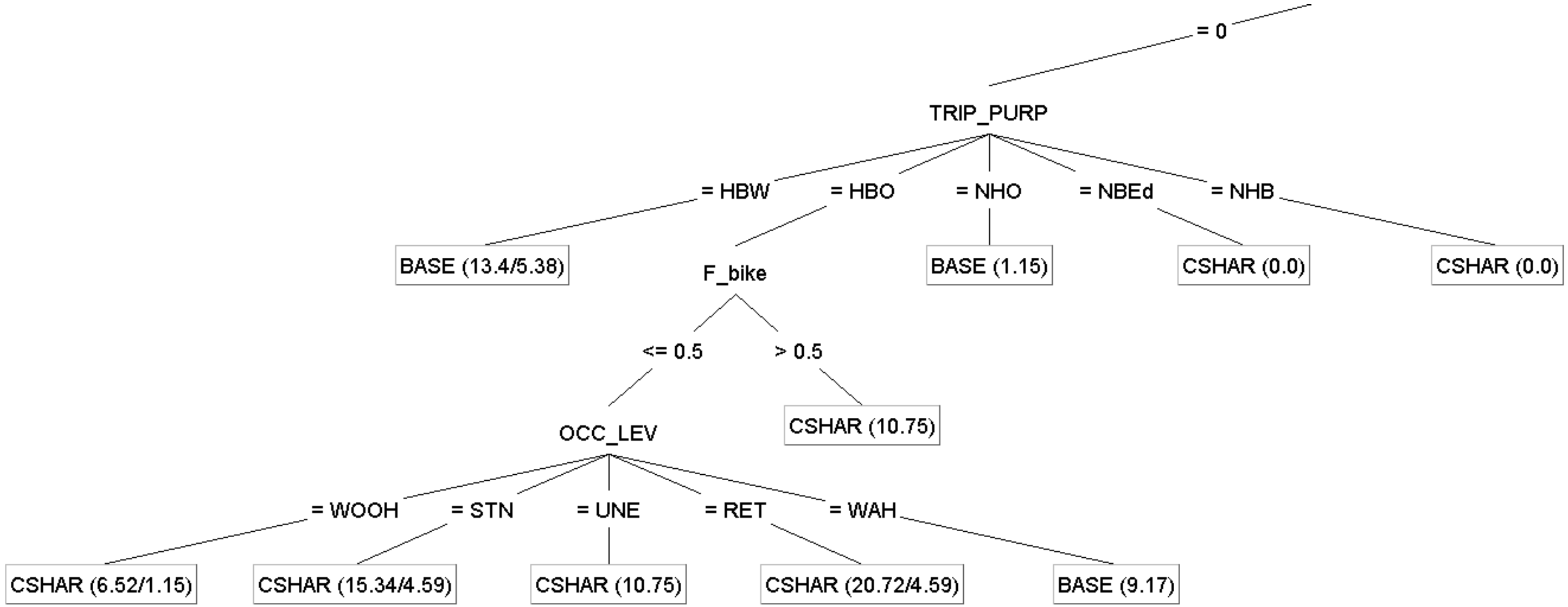


Figure 69. Subfigure III of the decision tree for the switching intentions from public transport to car sharing (relative values of trip attributes) (Figure 66)

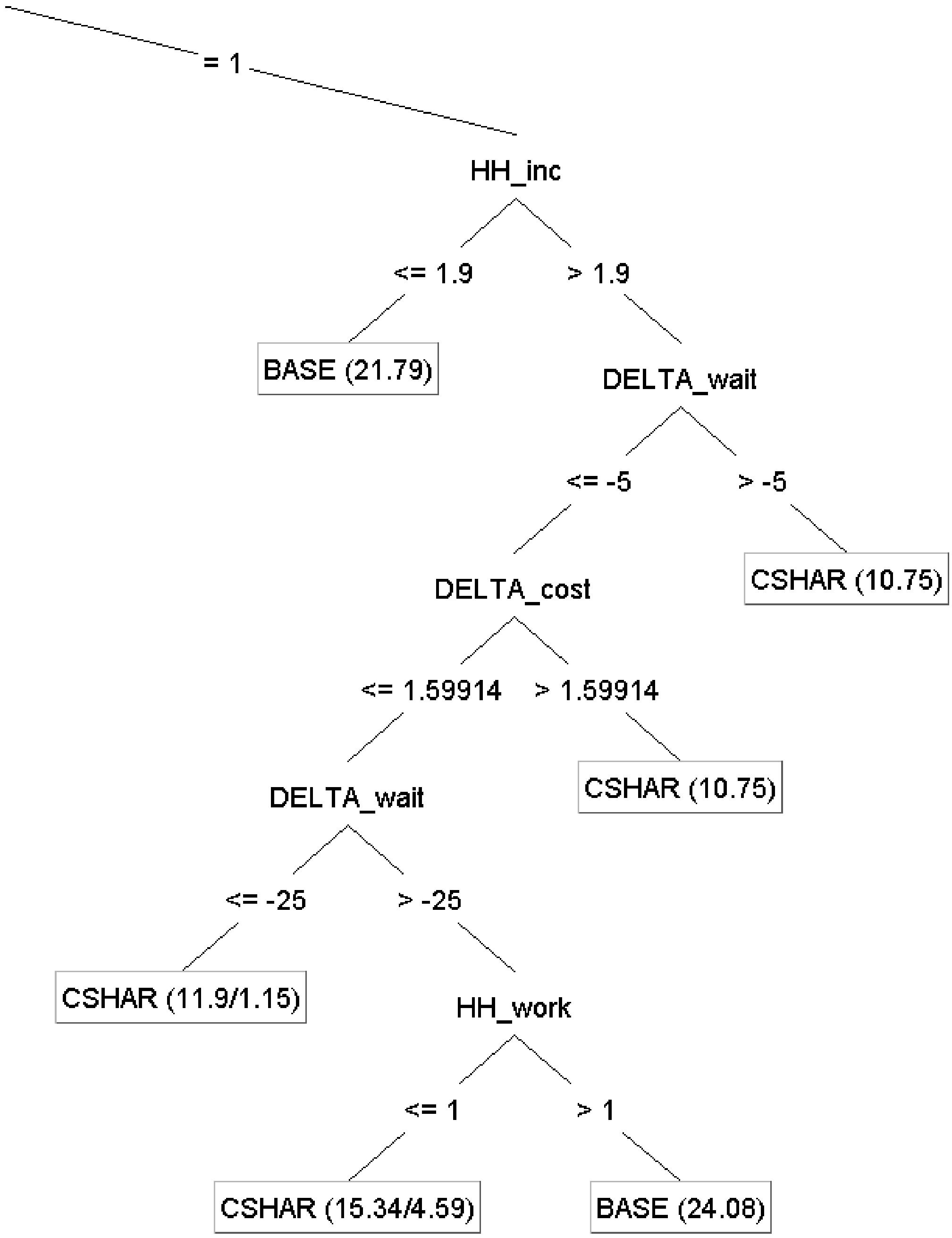


Figure 70. Subfigure IV of the decision tree for the switching intentions from public transport to car sharing (relative values of trip attributes) (Figure 66)

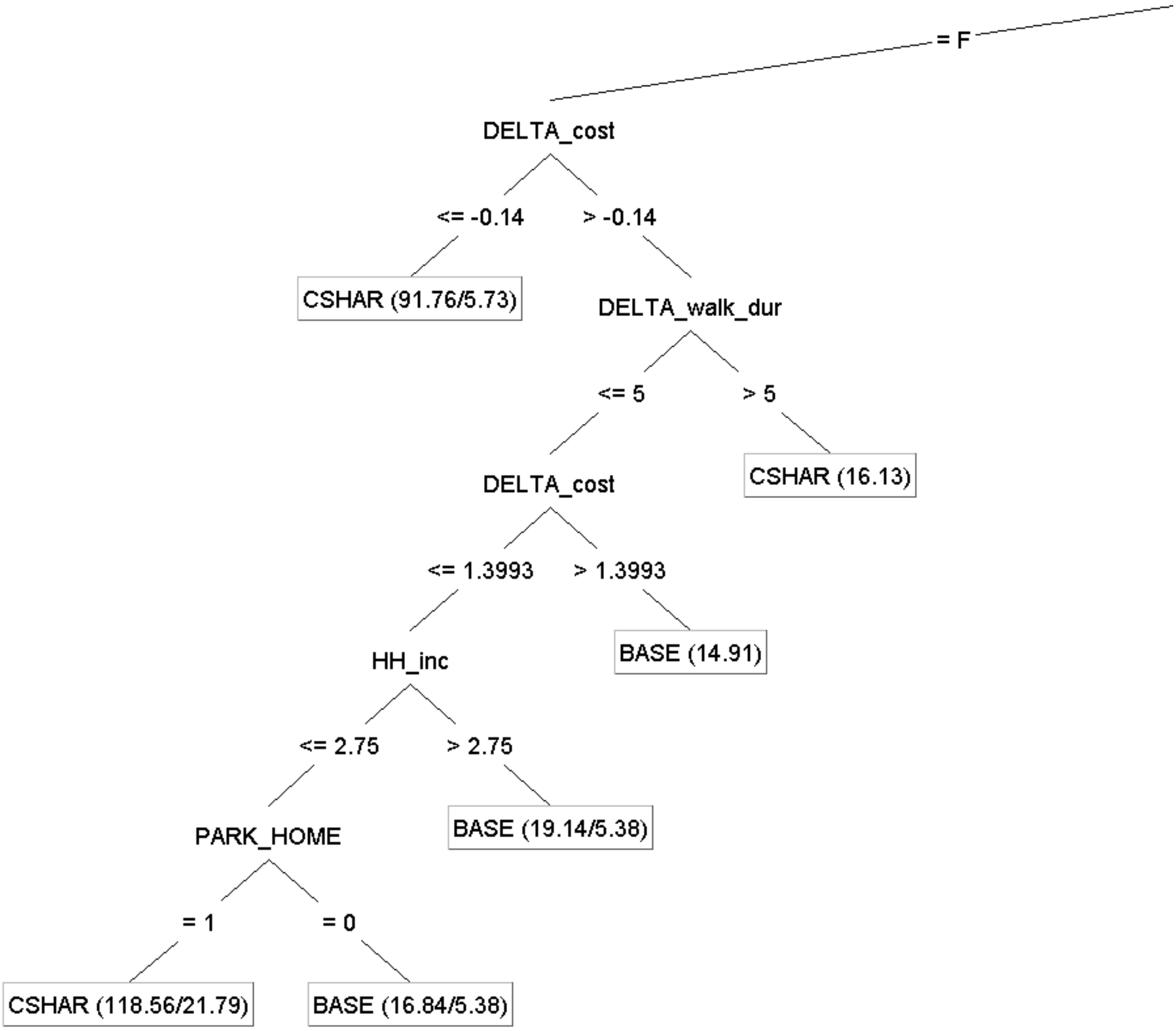


Figure 71. Subfigure V of the decision tree for the switching intentions from public transport to car sharing (relative values of trip attributes) (Figure 66)

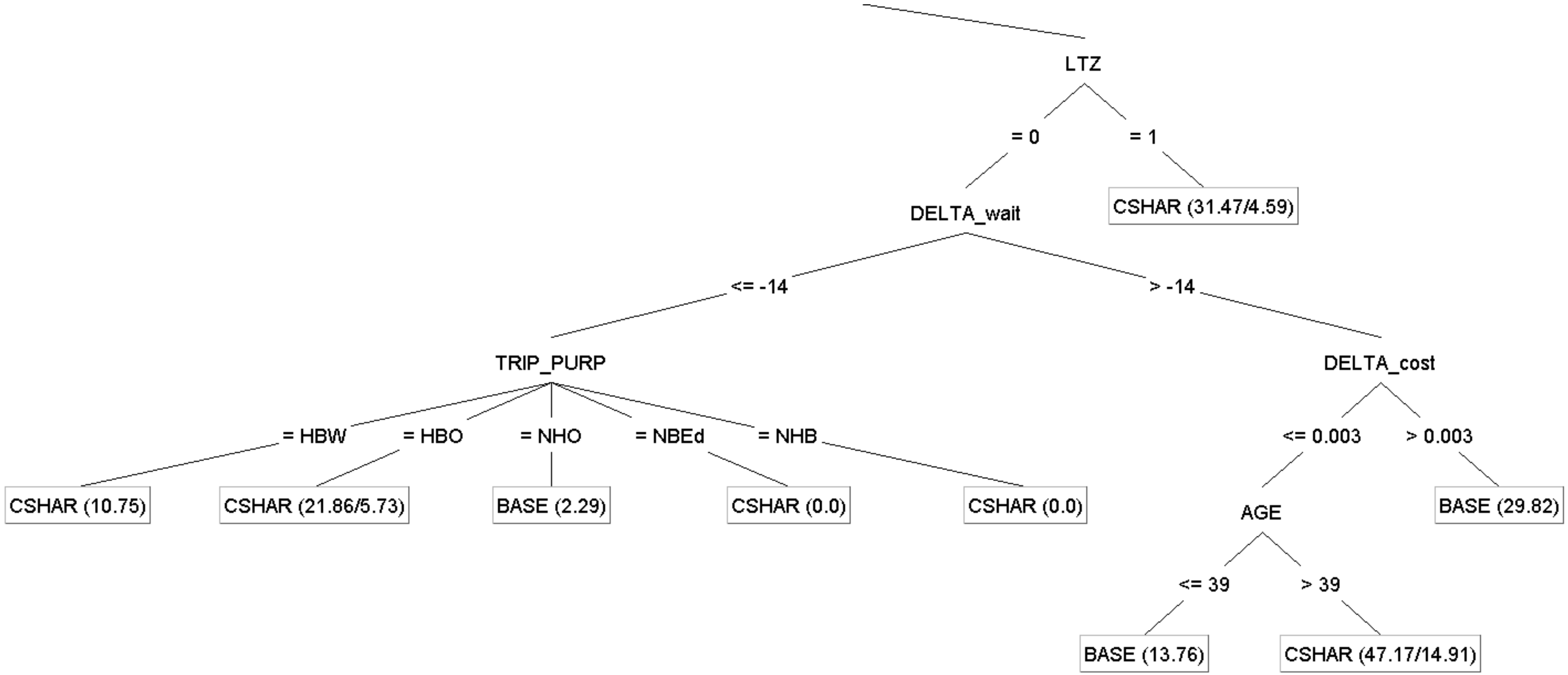


Figure 72. Subfigure VI of the decision tree for the switching intentions from public transport to car sharing (relative values of trip attributes) (Figure 66)

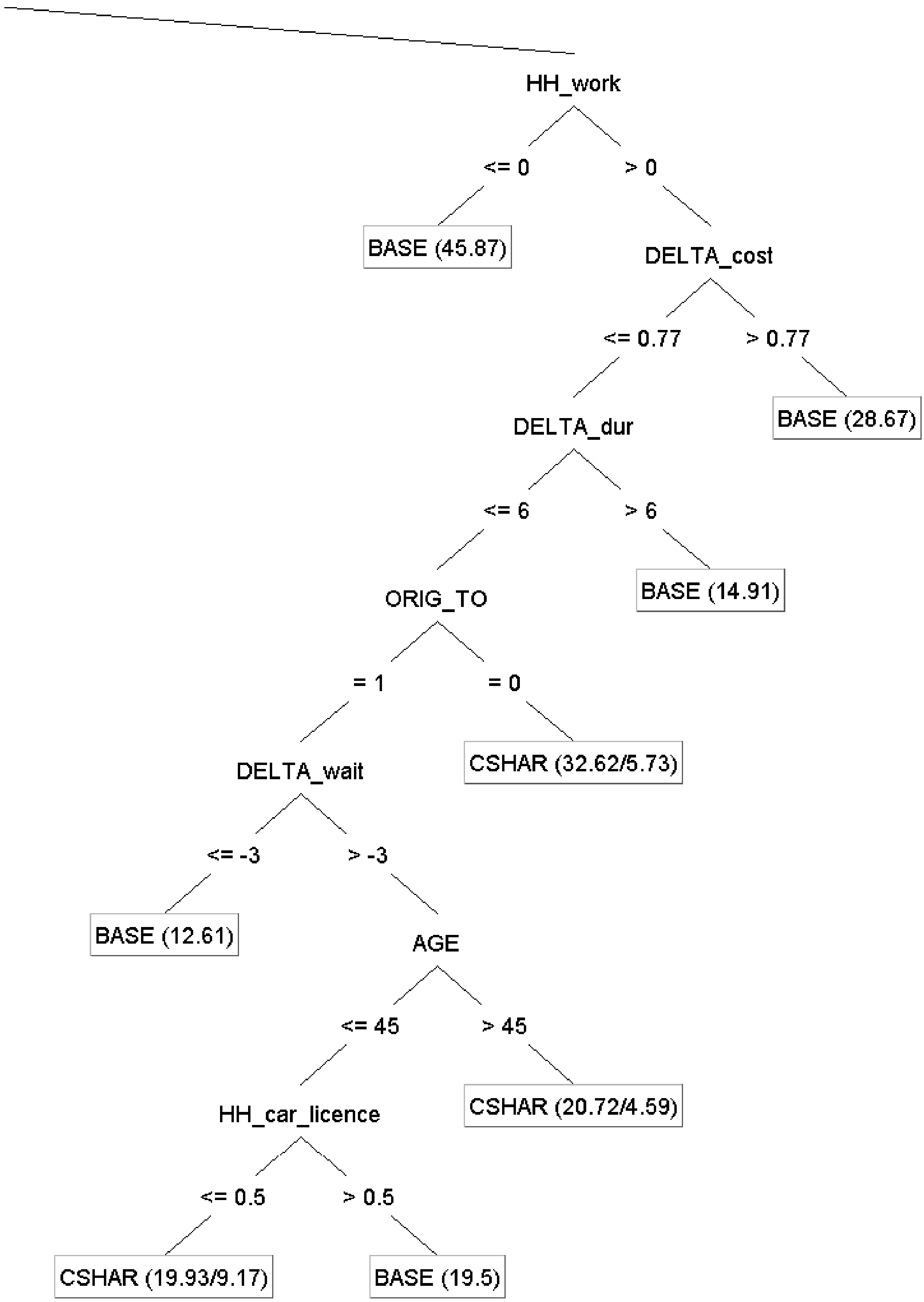


Figure 73. Subfigure VII of the decision tree for the switching intentions from public transport to car sharing (relative values of trip attributes) (Figure 66)

B.4 Switching model from bike towards car sharing

B.4.1 Absolute values of attributes of the alternative and the base mode

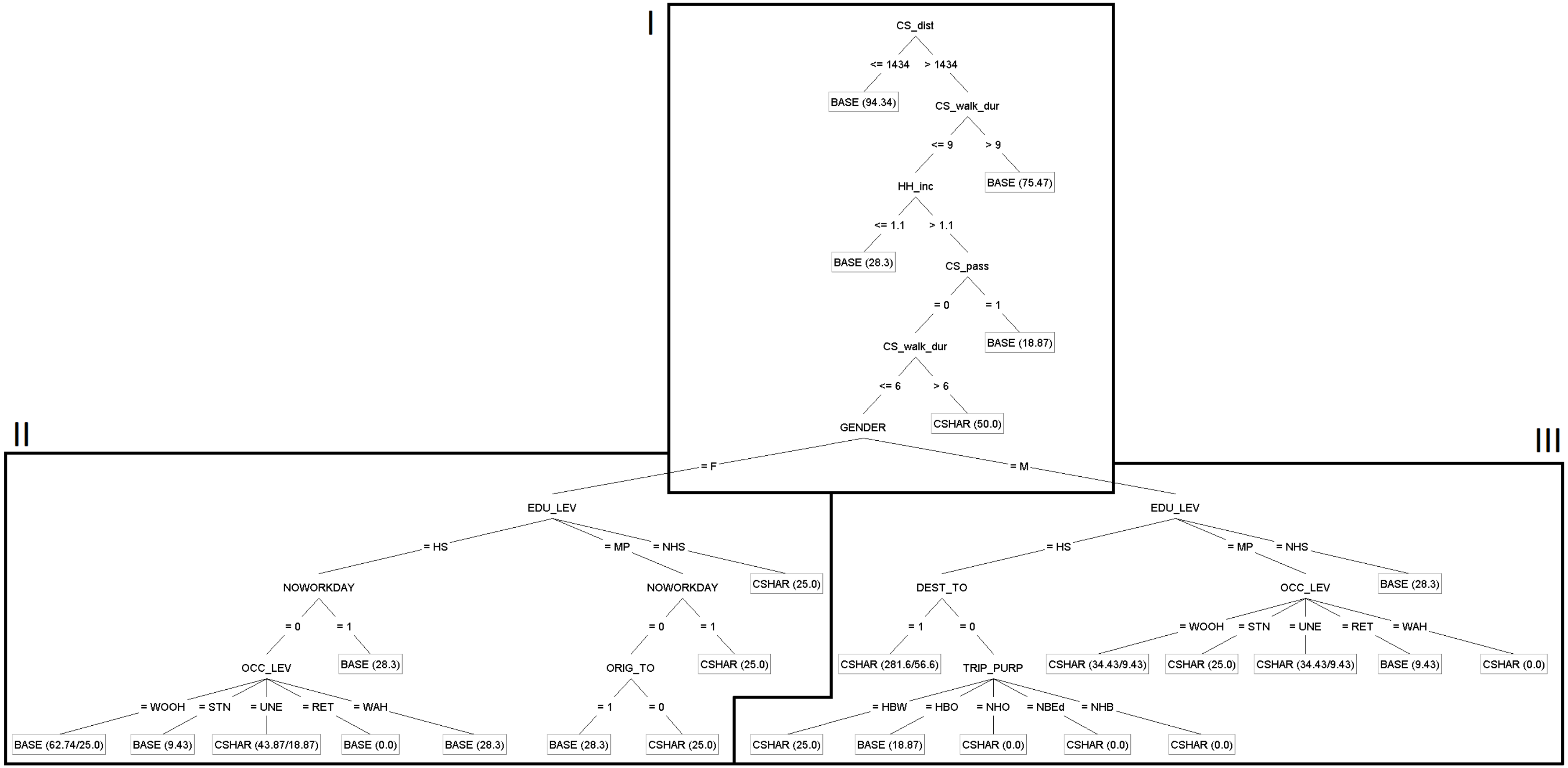


Figure 74. Decision tree for the switching intentions from bike to car sharing (numbered subfigures are shown in the following)

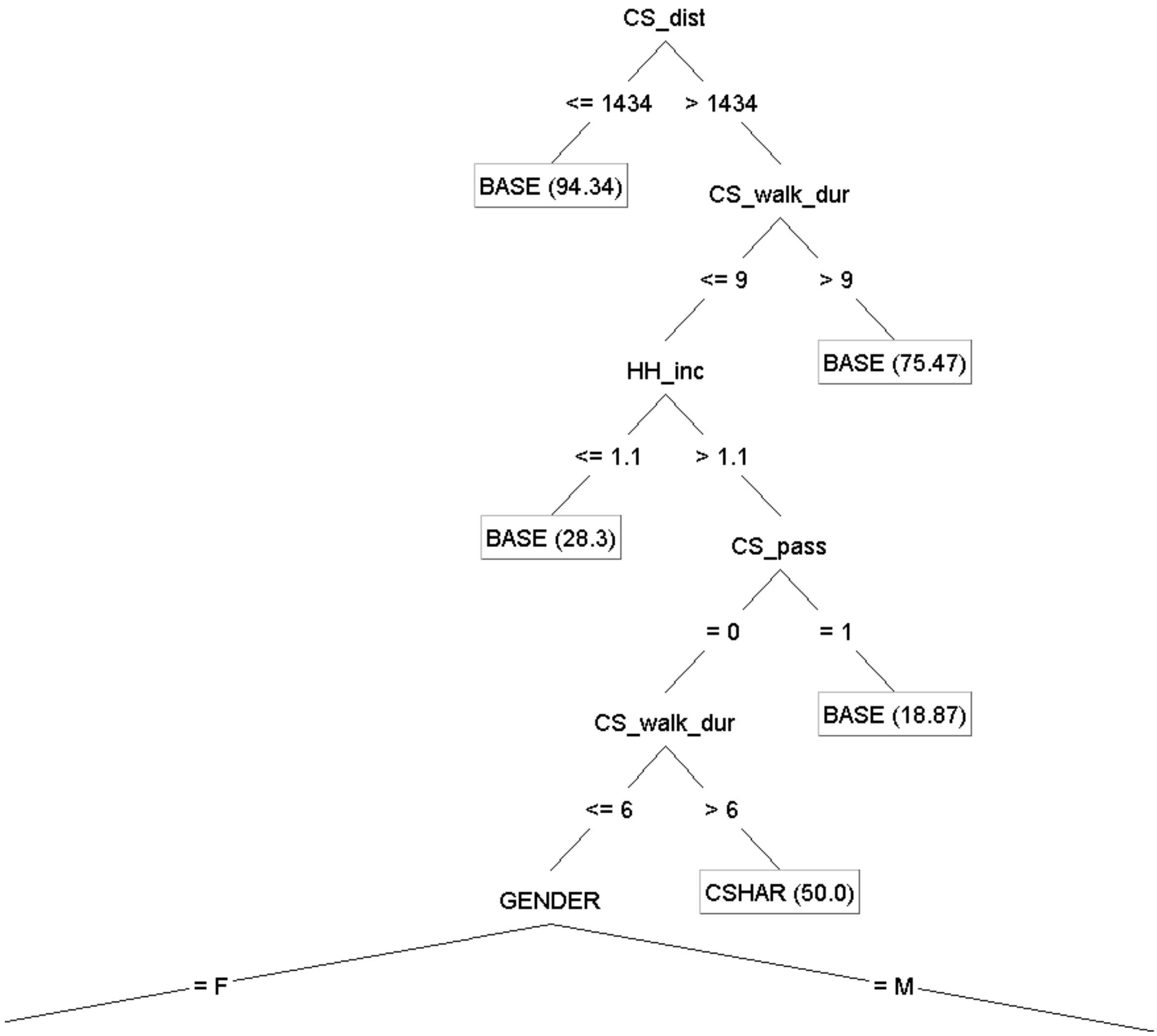


Figure 75. Subfigure I of the decision tree for the switching intentions from bike to car sharing (Figure 74)

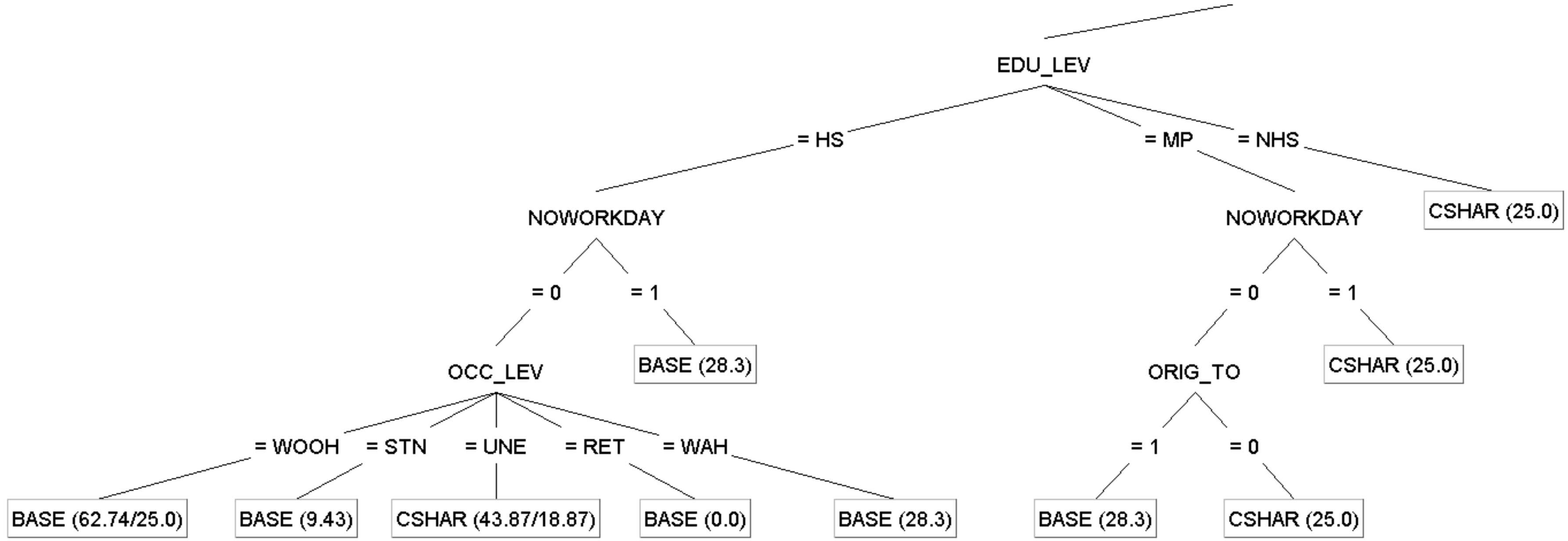


Figure 76. Subfigure II of the decision tree for the switching intentions from bike to car sharing (Figure 74)

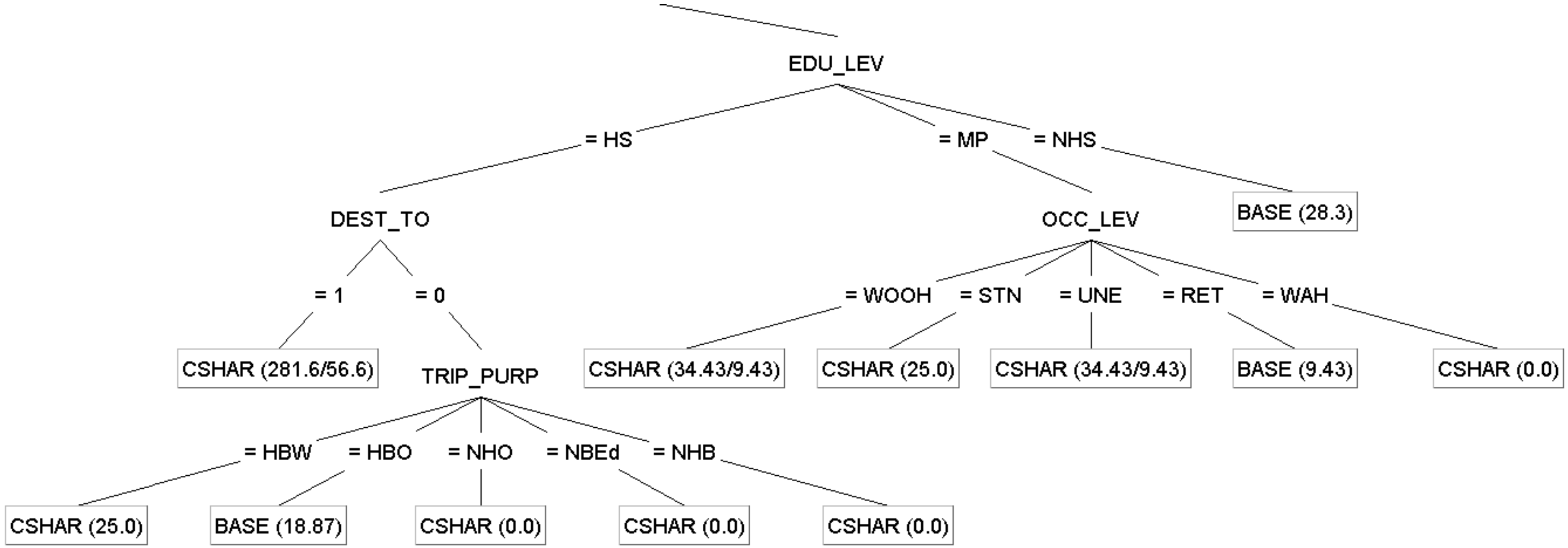


Figure 77. Subfigure III of the decision tree for the switching intentions from bike to car sharing (Figure 74)

B.4.2 Differences between attributes of the alternative and base mode

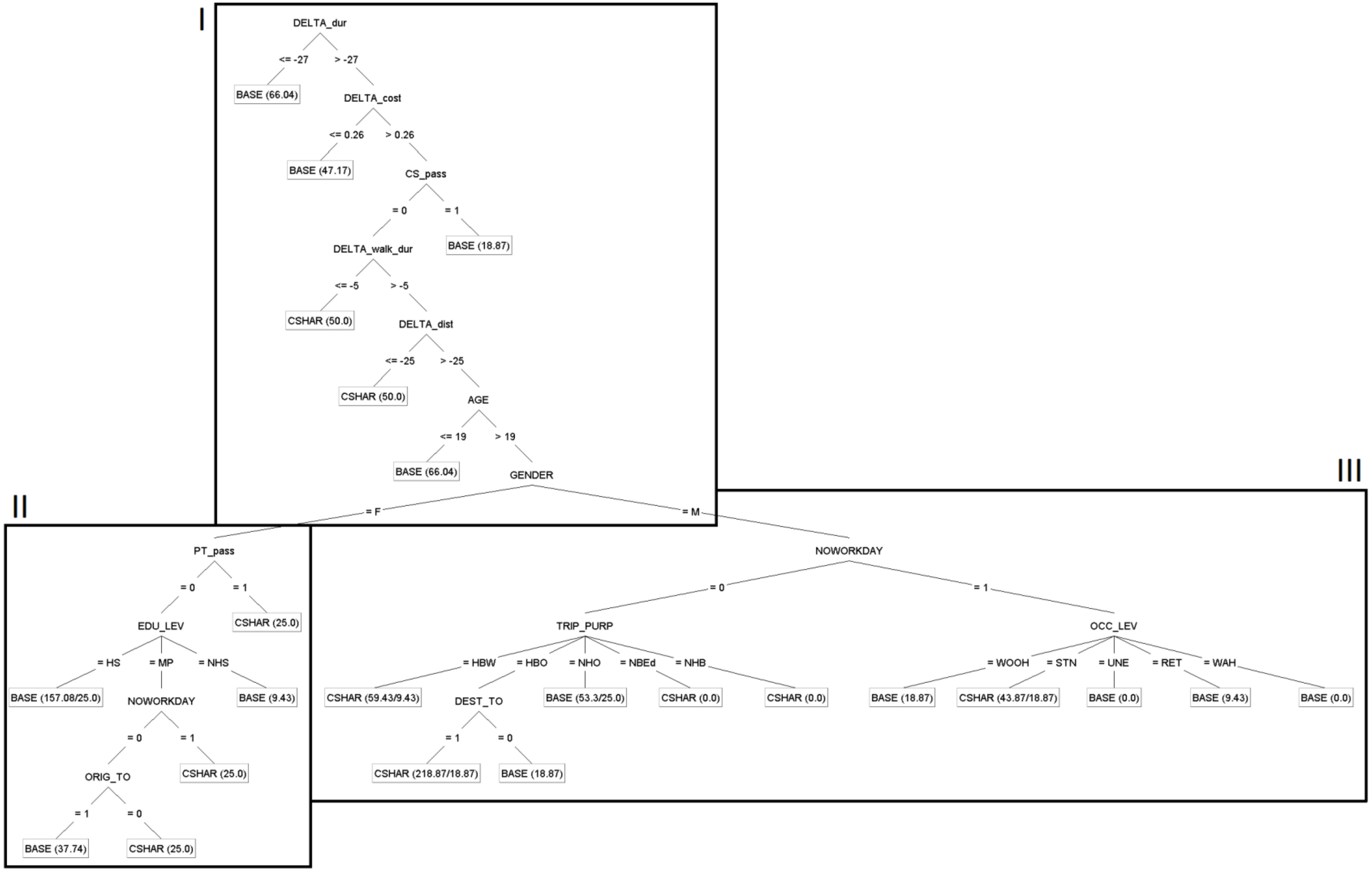


Figure 78. Decision tree for the switching intentions from bike to car sharing (relative values of trip attributes) (numbered subfigures are shown in the following)

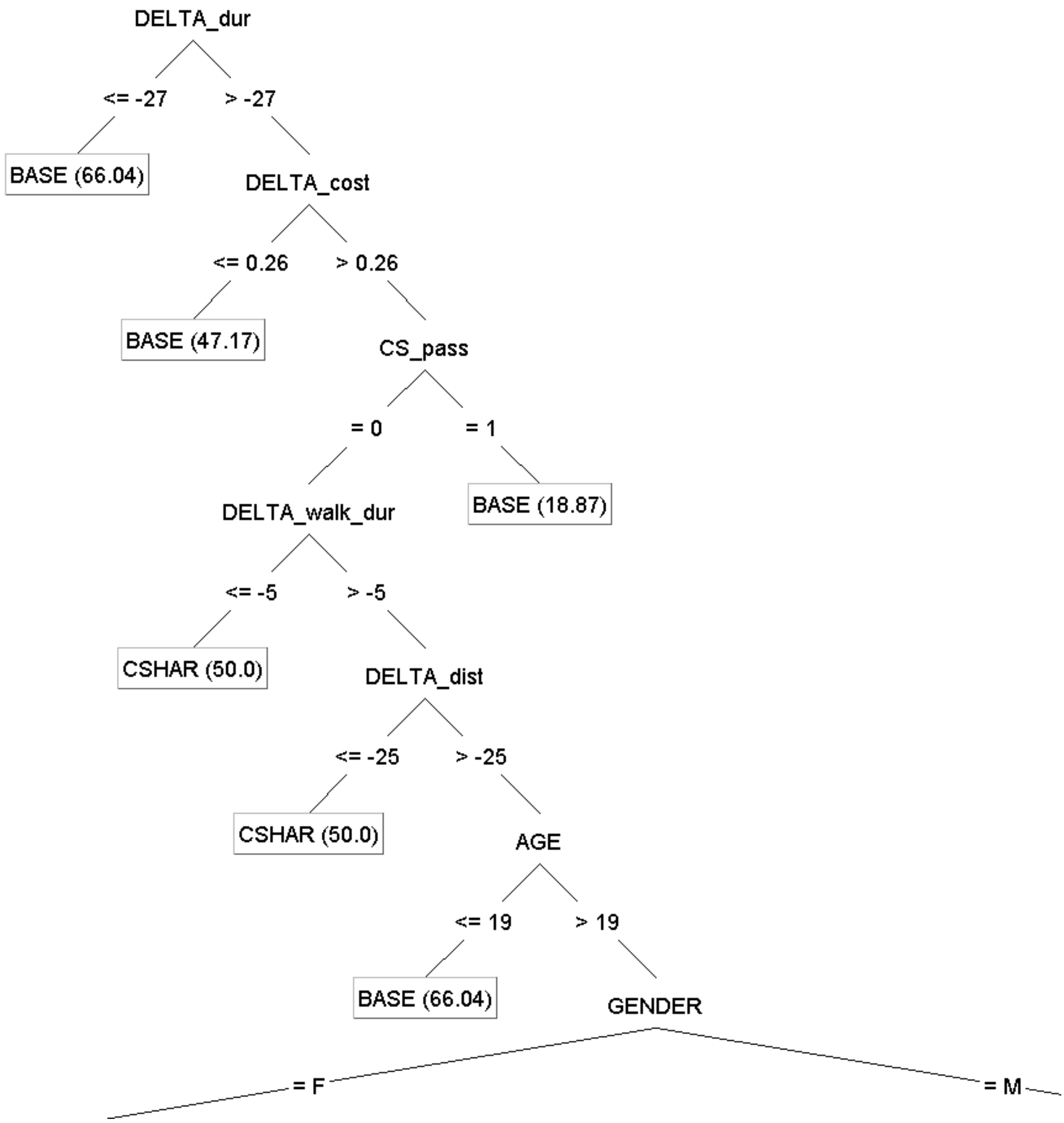


Figure 79. Subfigure I of the decision tree for the switching intentions from bike to car sharing (relative values of trip attributes) (Figure 78)

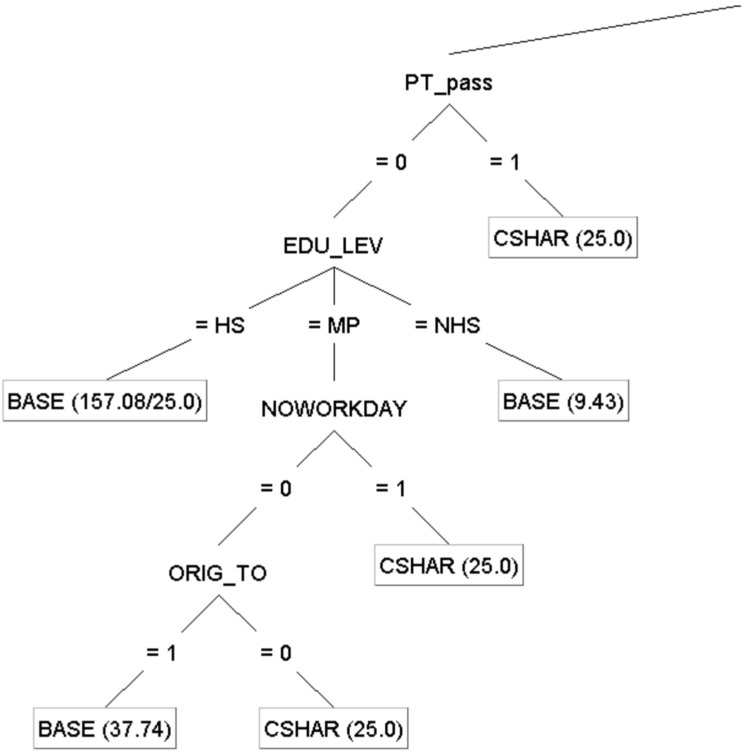


Figure 80. Subfigure II of the decision tree for the switching intentions from bike to car sharing (relative values of trip attributes) (Figure 78)

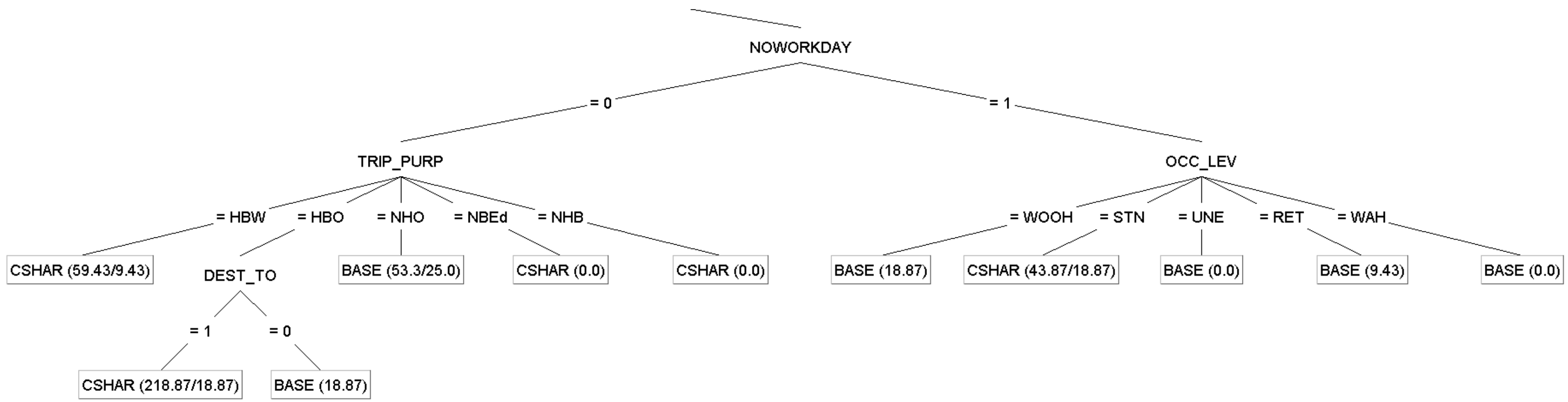


Figure 81. Subfigure III of the decision tree for the switching intentions from bike to car sharing (relative values of trip attributes) (Figure 78)

B.5 Switching model from walking towards car sharing

B.5.1 Absolute values of attributes of the alternative and the base mode

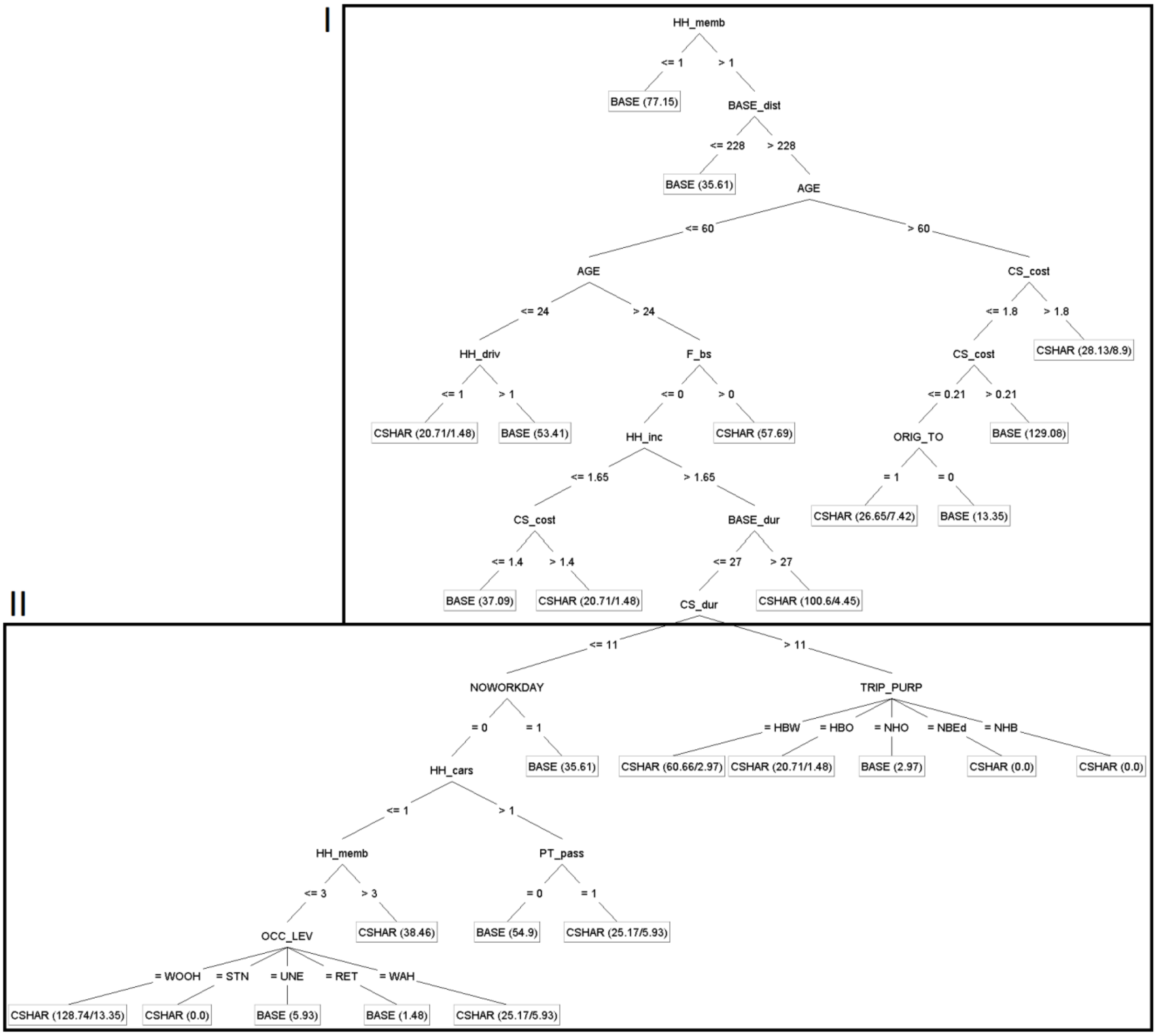


Figure 82. Decision tree for the switching intentions from walking to car sharing (numbered subfigures are shown in the following)

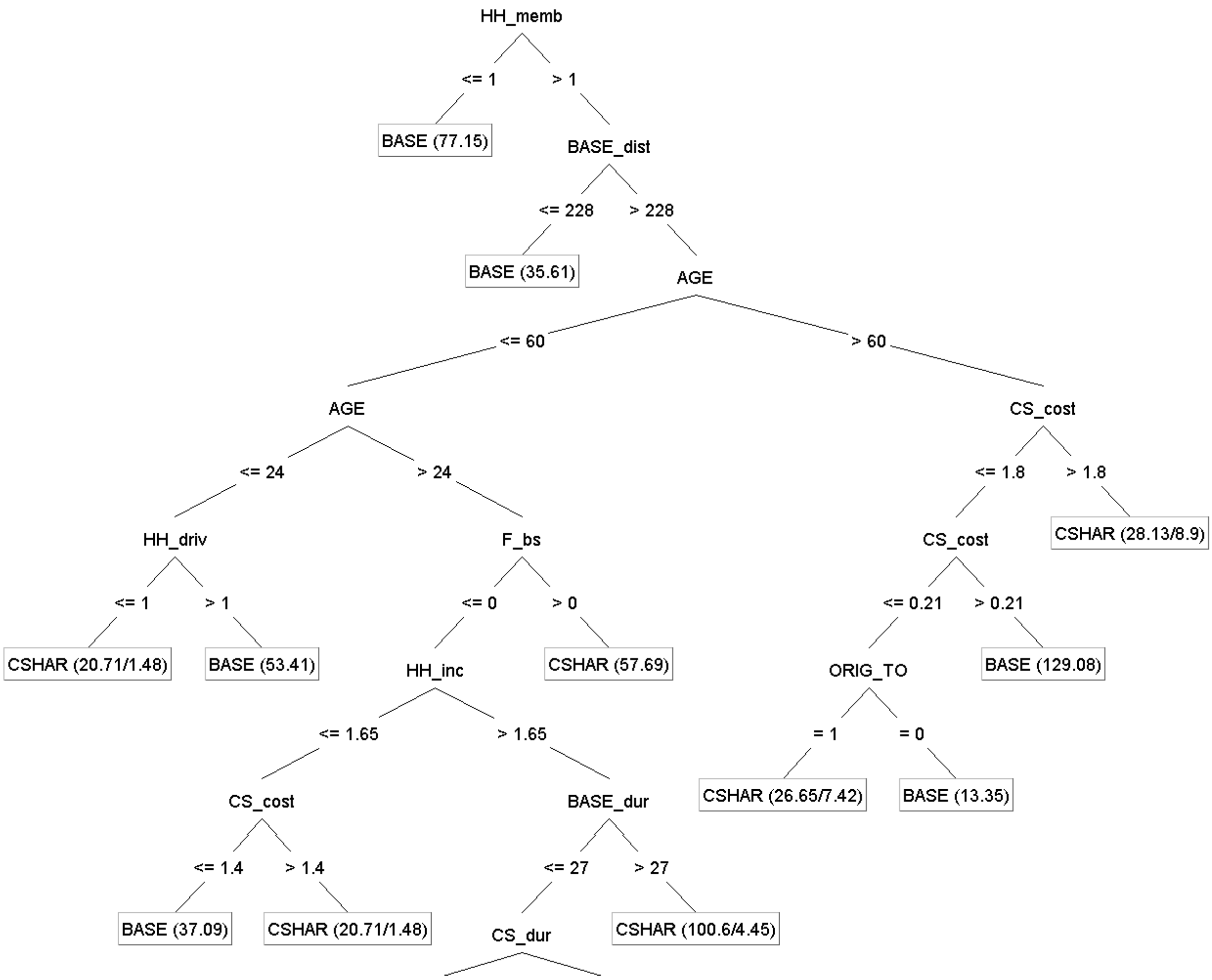


Figure 83. Subfigure I of the decision tree for the switching intentions from walking to car sharing (Figure 82)

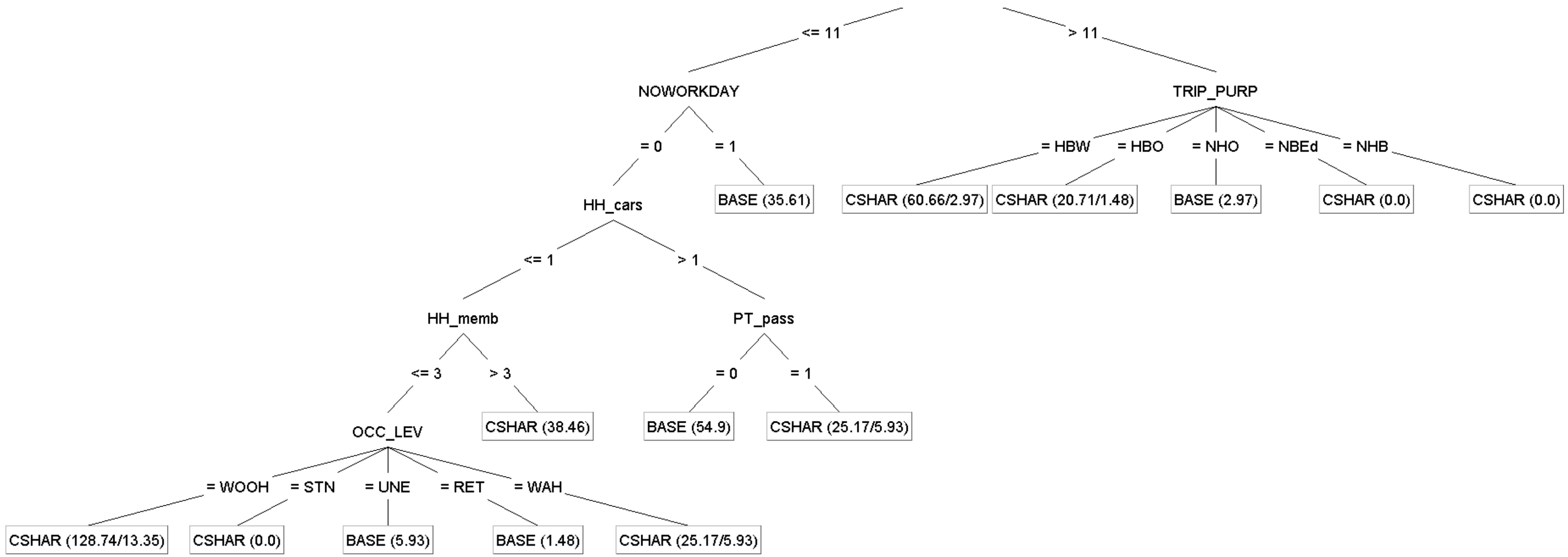


Figure 84. Subfigure II of the decision tree for the switching intentions from walking to car sharing (Figure 82)

B.5.2 Differences between attributes of the alternative and base mode

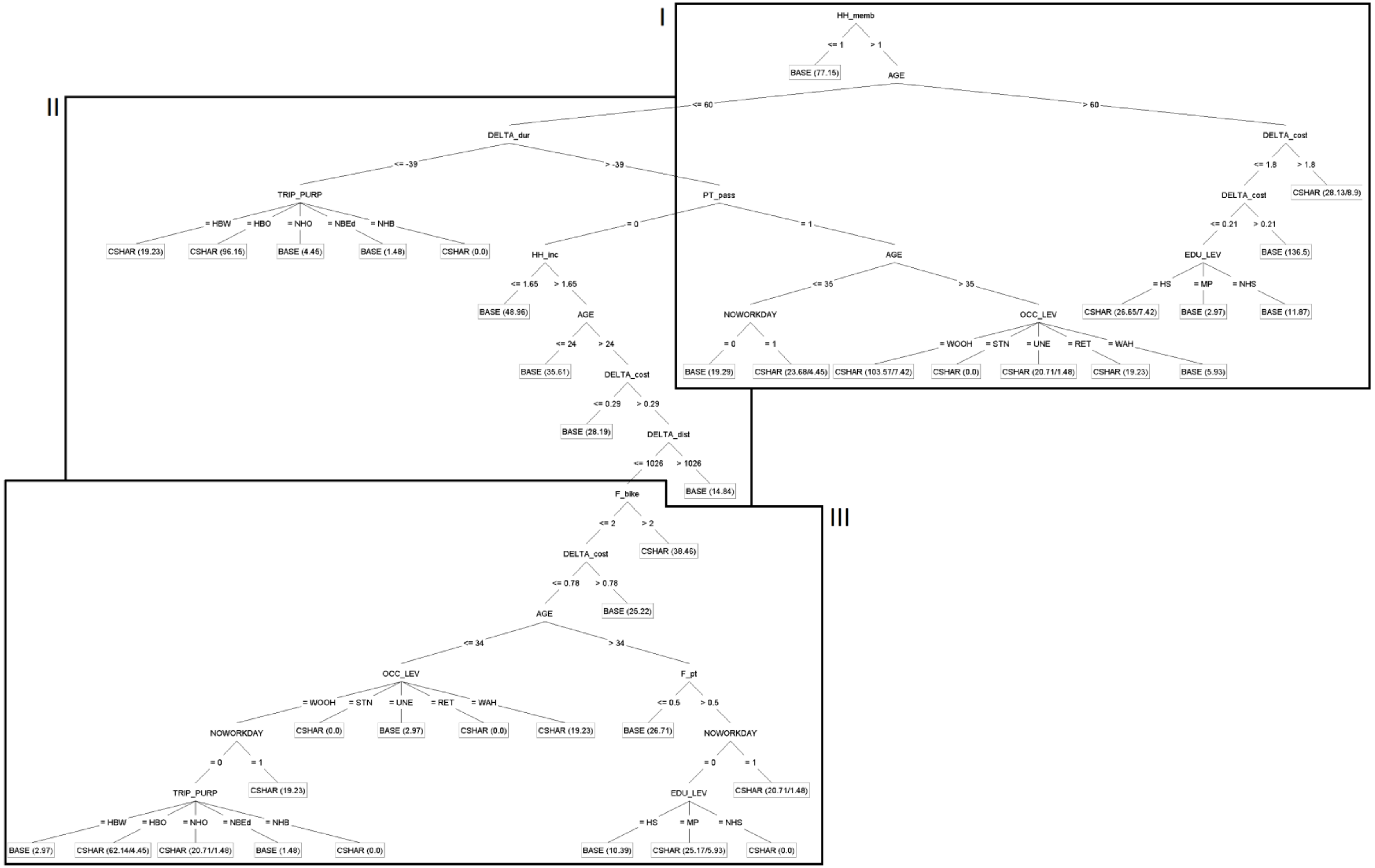


Figure 85. Decision tree for the switching intentions from walking to car sharing (relative values of trip attributes) (numbered subfigures are shown in the following)

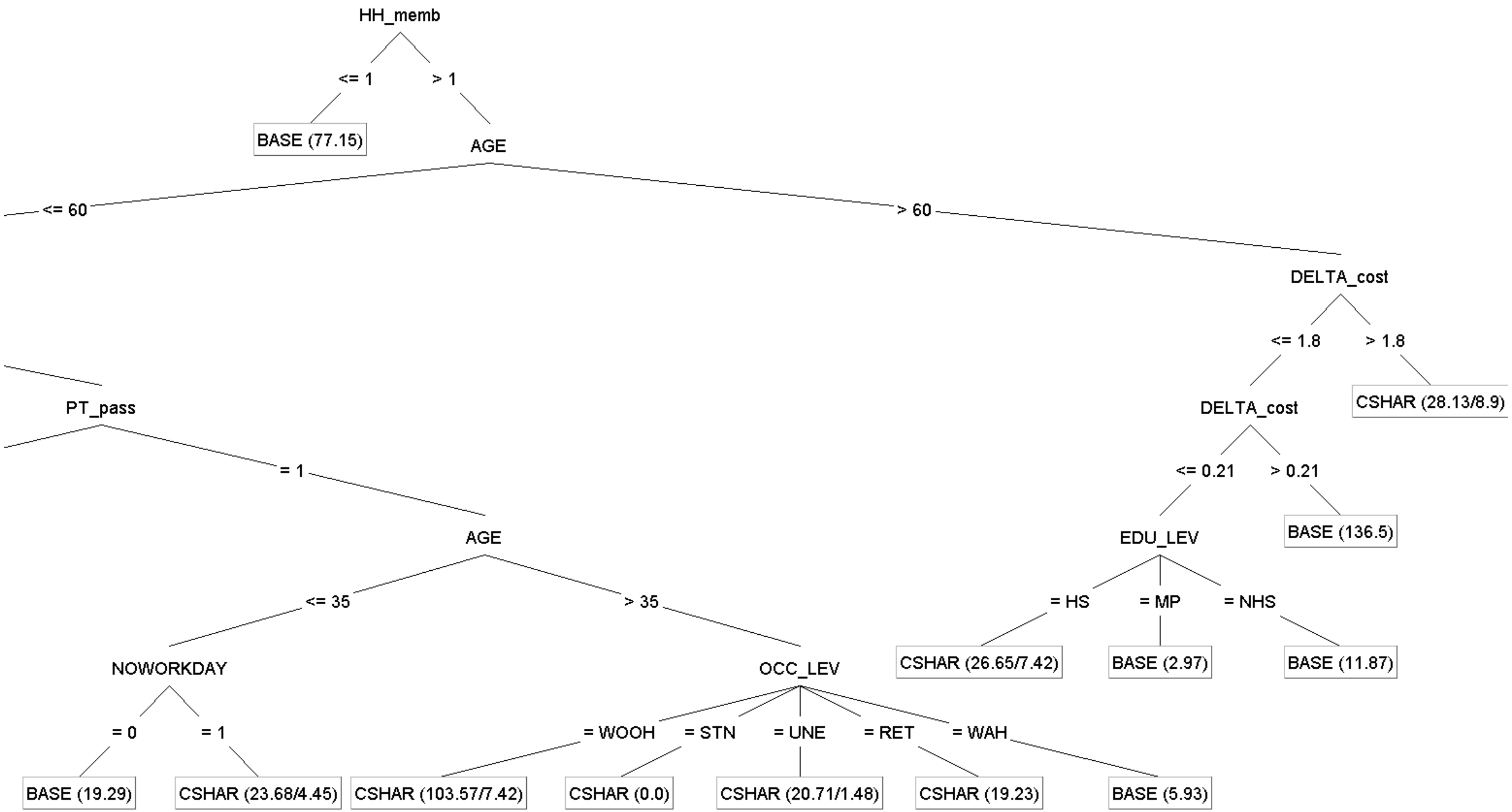


Figure 86. Subfigure I of the decision tree for the switching intentions from walking to car sharing (relative values of trip attributes) (Figure 85)

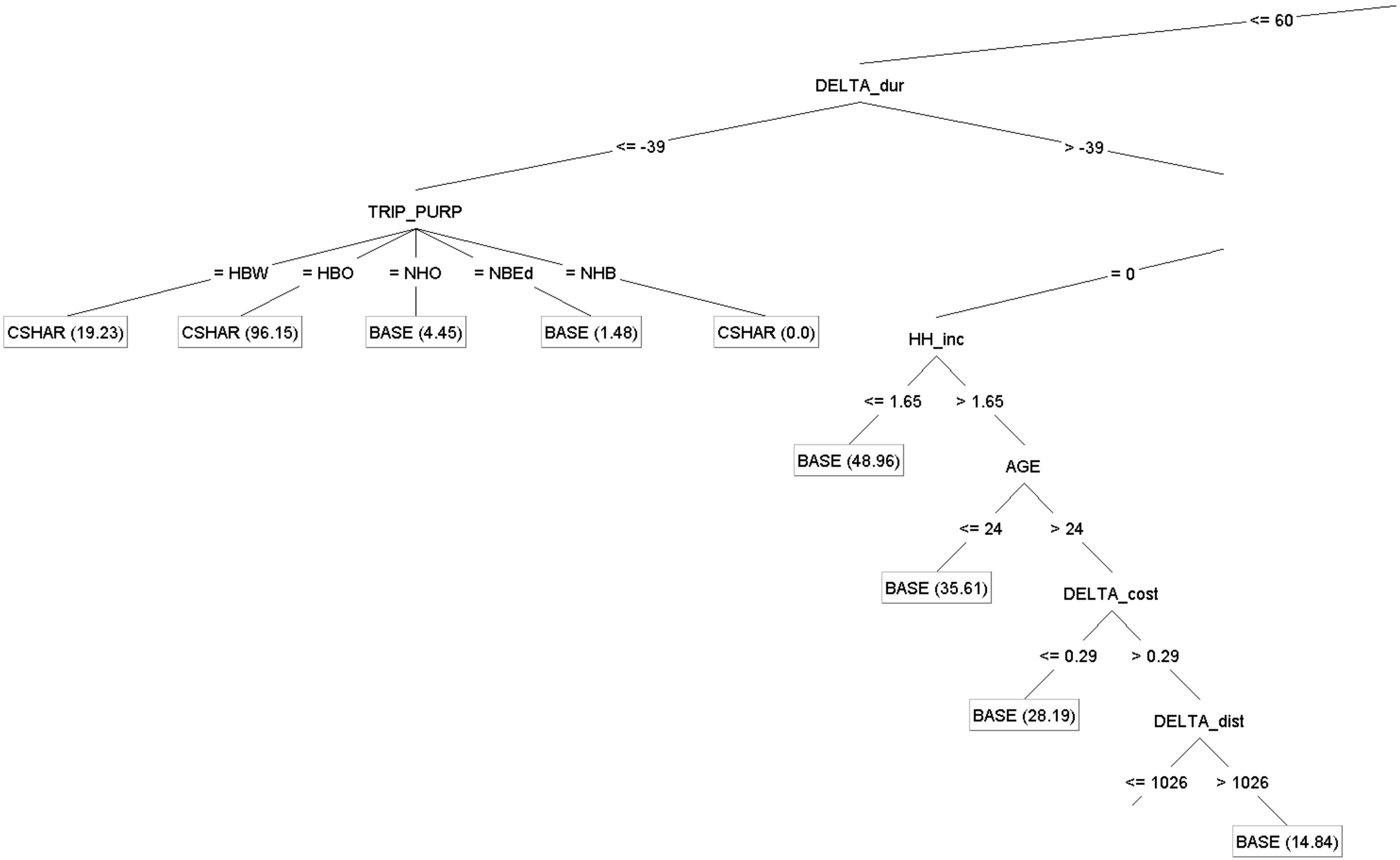


Figure 87. Subfigure II of the decision tree for the switching intentions from walking to car sharing (relative values of trip attributes) (Figure 85)

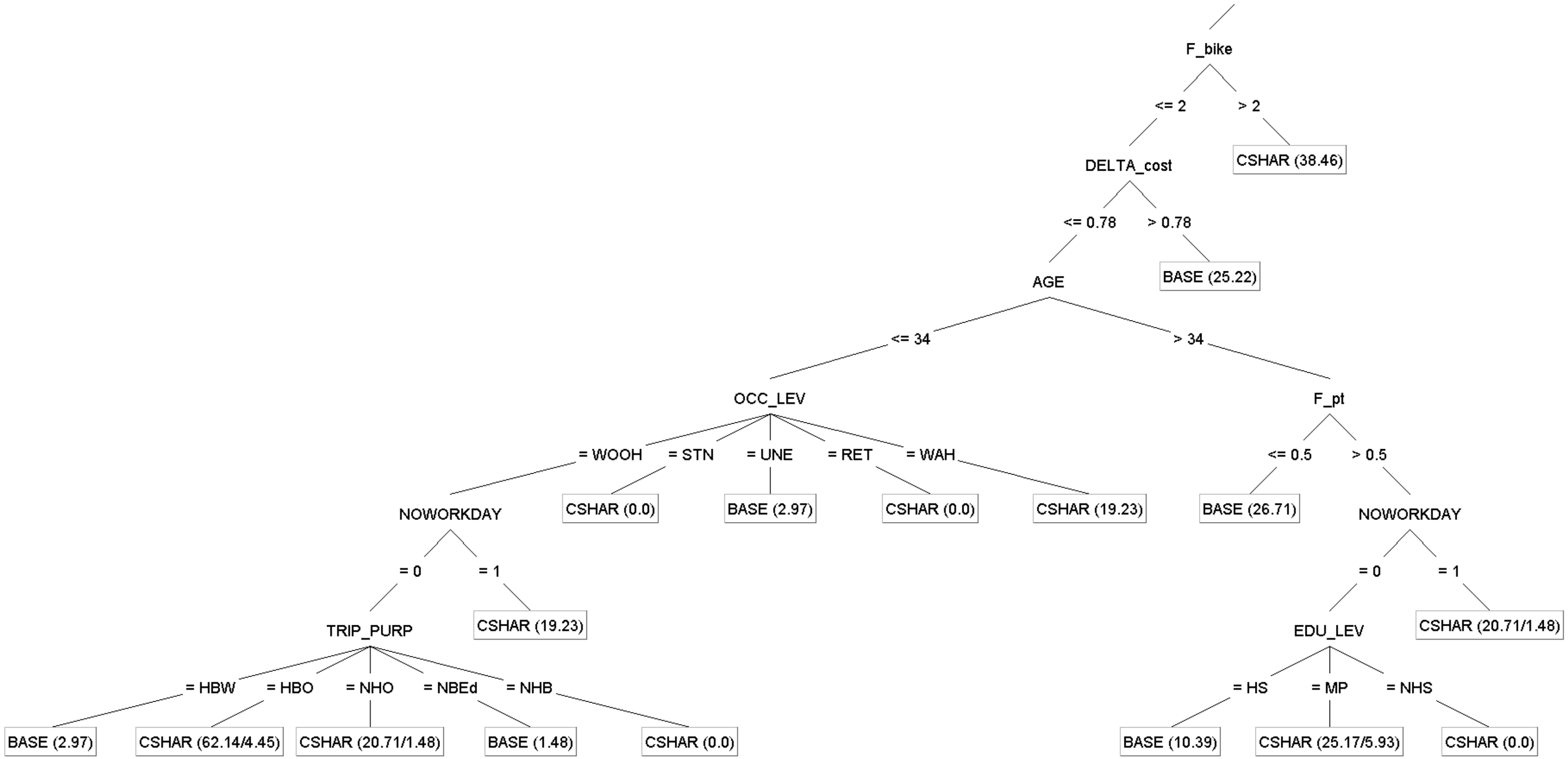


Figure 88. Subfigure III of the decision tree for the switching intentions from walking to car sharing (relative values of trip attributes) (Figure 85)