MASTERARBEIT

Titel der Masterarbeit

The Use and Effectiveness of Incentives for Reallocation in Bicycle-Sharing Systems

verfasst von

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Preface

First of all, I would like to thank my parents who supported me throughout my studies and made them possible for me.

Furthermore, thanks to my sister, grandparents as well as all my friends and my new brother-in-law, who accompanied and were there for me all these years.

Last but not least, I want to express my thanks to all people, especially my supervisors, who helped me with this master thesis by finding as well as concretizing the topic, giving advice and proof-reading.

Thanks to all of you and enjoy reading!

Outline

Figures

Tables

Table of variables

A .... Arrivals

a .... Station

(a,b) .... Trip for a pair of stations

b .... Station

c .... Marginal costs

D .... Demand

Dep .... Departures

E .... Area in the system

F .... Area in the system

K .... Capacity of stations

k .... Day parts

N .... Number of vehicles

S .... Set of stations

t .... Time (steps)

T .... Time period

w .... Binary variable of weekday and weekend

z .... Ordered set of values greater than zero

Λ .... Average number of arrivals

λ .... Arrival rate

$\frac{1}{\mu}$ .... Average trip time

Abbreviations

BSS	Bike-Sharing Systems
CLASSIC	Classic pricing policy
EFA	Exploratory Factor Analysis
EUR	Euro(s)
FCFS	First Come First Serve
FLUID	Fluid heuristic pricing policy
GPS	Global Positioning System
KMO	Kaiser-Meyer-Olkin
PBS	Public Bicycle Sharing

1. Introduction

The need to offer sustainable and environmental friendly modes of transport has become more and more relevant for city governments. Bicycling is a clean, cheap and quiet way to achieve this goal and might even present a faster mode of transport for short-distances than cars or public transportation in big cities. Hence, encouraging the bicycle rate in cities has become an important aim. In this context, numerous cities have implemented bike-sharing systems (BSSs) or public bicycle sharing (PBS). These systems offer customers the service to rent bicycles at any station and to return it at any other one. Mostly, these systems are a very cheap type of transport and provide the service for free for an initial time period. Moreover, problems like traffic congestion, parking space requirements and roadway costs are also alleviated (McClintock 2002).

Due to gravitation and tide effects as well as the one-way nature of most trips in BSSs, the systems become unbalanced over time. This means that stations may be full or empty, which in both cases lower the performance of the whole system. The master thesis at hand deals with the distinct reallocation methods for PBS. Especially, agent-based methods, in which the users rebalance the system, are of interest. As users are often not aware of the balancing problem in the system and do not reallocate the bicycles on their own, incentives can be employed to make users help to improve the performance of the system.

This thesis aims to summarize the theoretical and practical state of art of reallocation in BSSs and the effectiveness of incentives in them. As the title suggests, the focus lies on the determination how incentives may be used in agent-based reallocation techniques and if they are effective. Incentives have hardly been employed practically to rebalance BSSs so far. However, several studies and simulations have been conducted to evaluate their effectiveness. Likewise, in this thesis the potential usage of incentives is analyzed and an empirical research is conducted to determine the potential influence of a variety of incentives in agent-based reallocation methods. In the following it will be shortly explained how the master thesis is structured to reach the set goals in a most logical way.

1.1. Outline of the thesis

The thesis consists of seven chapters. In the first chapter an overview about public bicycle systems, their development and important definitions are listed, to outline the overall topic. Furthermore, the problem will be approached and research questions stated.

In the second chapter static and operator-based dynamic reallocation methods in BSSs are listed. These models, simulations or decision-support systems are extracted of literature and give an insight in the current state of science regarding this topic.

Agent-based reallocation methods are separately dealt with in the third chapter of this master thesis. As mentioned above, the focus lies on rebalancing of BSSs through incentives, hence, users. Therefore, agent-based reallocation methods and simulations, which have already been elaborated in literature, are of substantial interest to this thesis. Consequently, the existing methods are explained in more detail than static or operator-based dynamic reallocation methods.

Fourthly, the reader will get an overlook about the definition, characterization and general use of incentives. Potential as well as existing employment of incentives in the rebalancing problem is discussed. Additionally, hypothesis regarding the effectiveness of distinct kinds of incentives for solutions of the given problem are elaborated. This chapter is substantially important with regard to empirical research setting.

In the following chapter the building of the questionnaire, which was used for empirical research, is explained. Reasons for question involvement or deletion, as well as for employed answer options are given. Furthermore, the sample, sampling process as well as sample size determination are described. The used data set is also described in chapter 5.

The sixth chapter is the core part of the empirical study. In this chapter the raw data is analyzed and the hypotheses are tested. All tests employed in the SPSS program and their results are listed. The interpretation of these results and their meaning to the hypotheses are also included.

Eventually, the major findings of the empirical research are summarized and practical implications are drawn in the final chapter. Based on the gathered knowledge due to literature review and self-conducted empirical research, the research questions are answered. To complete the thesis, research limitations as well as a future outlook are given.

1.2. Bicycle-Sharing systems

The concept of BSS was developed in the 1960s. However, at the beginning a lack of technology in tracking bikes made their performance non-efficient (DeMaio and MetroBike 2009, p. 41). The development of BSSs has gone through three generations. These can be seen in figure 1.

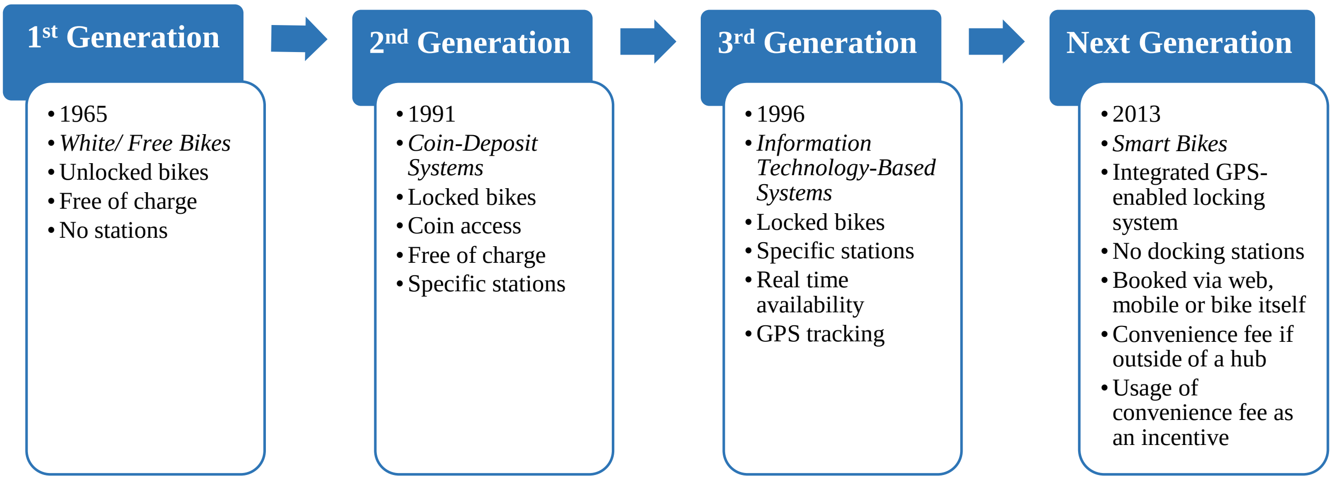


Figure 1: BSS' generations (Source: Own creation based on Midgely (2011), DeMaio and MetroBike (2009) and Christensen (2014))

The first generation could be found in Amsterdam in 1965 (DeMaio and MetroBike 2009, p. 42). Ordinary bikes got painted white, hence this generation is also called *White Bikes* (Shaheen et al. 2010, p. 2), and were distributed for public use. Due to stolen and broken bikes the system did not last longer than a few days (DeMaio and MetroBike 2009, p. 42).

Twenty-six years later the second generation, also named *Coin-Deposit Systems*, offered better bikes in terms of tires and wheels with advertising plates. They could be rented with a coin deposit and returned only at certain stations throughout the central city. However, customers were still anonym which led again to a high amount of stolen bikes. (Shaheen et al. 2010, p. 2)

Therefore, the 3rd generation of BSSs alias *Information Technology-Based Systems* (Shaheen et al. 2010, p. 2) involved customer tracking. This was introduced at Portsmouth University in England in 1996. Students rented bikes with a magnetic stripe card. Furthermore, the new generation included electronically-locking racks or bike locks, telecommunication systems, smartcards and fobs as well as mobile phone access and on-board computers (DeMaio and MetroBike 2009, p. 42).

The fourth generation of PBS is in its development. Characteristics and improvements towards the 3rd generation may be flexible and clean docking stations, innovations regarding bicycle redistribution techniques, smartcard integration with other transportation modes (like public transport or carsharing) and further technological advances like GPS (Global positioning system) tracking, touchscreen kiosks and electric bikes. (Shaheen et al. 2010, p. 14)

The company Social Bicycles already provides the so called Smart Bikes which can be seen as the next generation of BSSs. These bicycles have integrated GPS-enabled locking systems on the bikes, which makes docking stations redundant. The bikes can be rented via web, mobile or the bike itself by entering a code. Due to this GPS-enabled locking system the bikes can also be returned outside of the provided hubs. However, a convenience fee has to be paid if they are locked somewhere outside of these stations. This convenience fee is provided as an incentive to other users, who might pick the bike up from its location. Hence, this generation already includes incentives for system balancing. (Christensen 2014)

Main lessons learned from the former generations are user anonymity produces bicycle theft and vandalism. Moreover, bicycle redistribution as well as real-time information systems on station parking and bicycle availability are necessary for a good performance. (Shaheen et al. 2010, p. 14)

In recent years, due to improved technology opportunities PBS have spread over the world. In 2010 there were approximately 100 BSSs in about 125 cities worldwide (Shaheen et al. 2010, p. 1). Their advantages are convenient first/last mile connection to other modes of transport and environmental-friendliness (DeMaio and MetroBike 2009, p. 41).

Today different models of provision exist. PBS may be operated by quasi-governmental transport agencies, universities, (non-)profit organizations or advertising companies (DeMaio and MetroBike 2009, p. 45). The operation of BSSs bears substantial expenses due to maintenance, distribution, staff, insurance, office space, storage facilities, website hosting and electricity (DeMaio and MetroBike 2009, p. 49). Moreover, the capital costs involved are even higher. Operating costs are on average about $1,600 per bicycle, while capital costs are estimated around $3,600 per bike (New York City Department of City Planning 2009, p. 4).

In this thesis the innovations in bicycle redistribution activities are of interest. Possible kinds of innovations are specially designed vehicles for bicycle relocation, automated technologies that facilitate demand-responsive bike relocation or agent-based techniques (already used in Vélib) (Shaheen et al. 2010, p. 16). The empirical part of the thesis at hand is put on the last opportunity mentioned.

1.3. Important definitions

In the following section some definitions which will be found in the thesis are explained.

In line with the literature review of reallocation methods *pull and push stations* will be mentioned several times. They describe docking stations of BSSs which have higher return rates than renting ones (pull stations) and vice versa (push stations). Therefore, pull stations have a tendency to be full, while push stations are often found empty. An example for push stations would be uphill located ones. Due to the increased effort of cycling uphill, these stations are mostly used for rental. However, stations can change from pull to push stations due to time of the day, working or weekend day, season or other factors. For example, some stations are favored for rental in the morning and preferred for giving bikes back in the evening. Hence, this station would be a push station in the morning, but a pull station in the evening.

Second, *symmetric and asymmetric systems* in terms of public bicycle programs are of interest. Symmetric systems means symmetric demand. Hence, there are no pull or push stations and the flow of bicycles between two stations is identical in both directions. However, these systems are only existent in theoretical background. In practice all programs are asymmetric. Mostly, symmetric systems are thought to rebalance themselves in literature. Only the study by Fricker and Gast (2014) concludes that rebalancing is needed for both kinds of systems. They show that the performance of symmetric systems is also poorly without any reallocation methods (Fricker and Gast 2014, p. 10).

Another important definition to make is for the terms *agent-based* and *user-based*. These terms will be used synonymously. In the context of this work, agent-based reallocation techniques means that the rebalancing of a BSS is conducted through its users. Hence, customers of the system themselves rebalance the PBS, instead of the system's staff, which is the case in operator-based reallocation methods.

An *optimum equilibrium* in the context of PBS is defined by a demand pattern in which each outgoing trip is balanced by an incoming trip. Hence, the inventory levels remain stable (Papanikolaou 2011, p. 129). In practice this is hardly possible, but a useful assumptions for theoretical modelling. Hence, the theoretical nature of optimum equilibrium has to be kept in mind.

1.4. Problem definition

The problem approached results from the random user demand in BSSs. In these systems users arrive at a certain docking station, rent a bicycle for an unknown time period and then return it to the same or different station. Due to location, weather, time, season or other factors pull- and push stations are formed. Furthermore, PBS are mainly used for medium and short distances as well as for one-way trips. Therefore, the system becomes unbalanced over time (Caggiani and Ottomanelli 2012, pp. 203).

The main strength of a BSS (its convenience) is based on its ability to meet the demand in bicycles and available docking stations. However, this demand is complex and stochastic due to arrivals at the stations, distinct origin-destination pairs and trip lengths. Moreover, if the system is unbalanced and full/empty stations are already existent, further stochastic demand due to users who look for available bikes or docking stations develops (Fricker and Gast 2014, p.2).

An unbalanced BSS leads to substantial costs for the operator. First, a temporary loss of customer due to empty stations has to be registered. Furthermore, a loss of quality of service and performance leads to a permanent loss of users, which has long-term effects. Customers become unsatisfied if their demand is not met and alternative transport options are used.

Therefore, the problem is the unbalance of BSSs. The aim is to keep PBS balanced and, hence, ensure a good performance of the system, minimize the costs for the operator and keep users satisfied. The obstacle can be solved in two ways: operator- or user-based (Caggiani and Ottomanelli 2012, pp. 203). The different reallocation methods are displayed in figure 2.

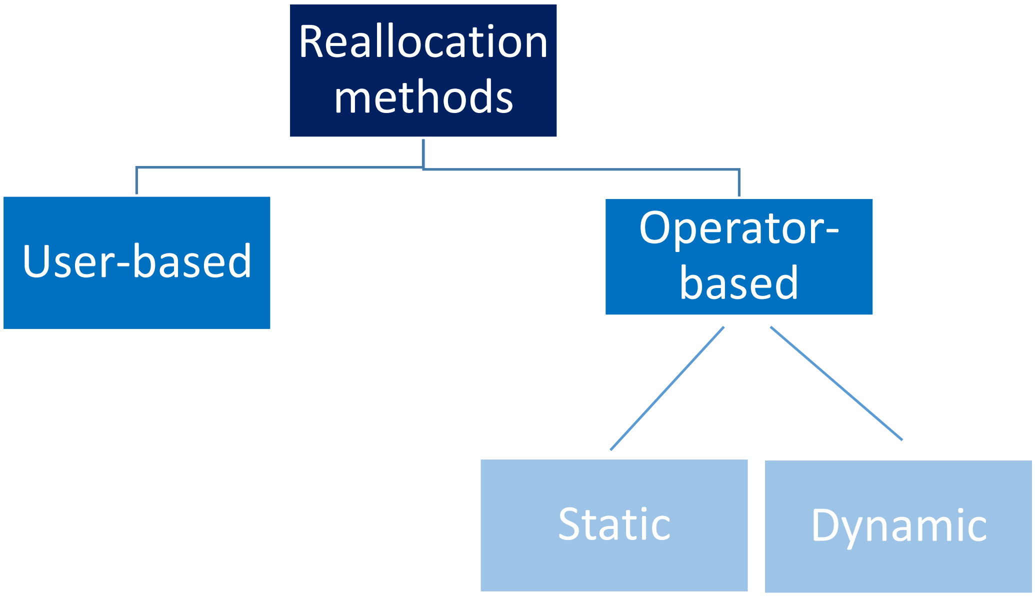


Figure 2: Types of reallocation methods (Source: Own Figure)

User-based techniques involve the customers, who might collaborate in balancing the system. These user-based techniques are also called agent-based and will be discussed in detail in chapter 3. Operator-based balancing activities (discussed in chapter 2) are conducted by the system's staff. Mostly a fleet of vehicles, which moves bikes from pull to push stations is involved. While operator-based reallocation techniques are feasible for short terms, agent-based activities are effective for mid-term periods (Caggiani and Ottomanelli 2013, p. 204).

Operator-based reallocation techniques can be further divided into static and dynamic ones. In case of static methods user demand is neglected. Hence, situations, in which (almost) no activity in the PBS takes place, are considered. These situations may be during night. The main aim for static methods is to establish an efficient fleet allocation which can serve (most of) the demand until the next reallocation activity is planned. Dynamic rebalancing techniques are done during customers use the system. Therefore, not also the historic and forecasted, but also the current demand plays an important role in calculating the number and ways of rebalancing.

As the title *the use and effectiveness of incentives for reallocation in bicycle-sharing systems* suggests, the aim of this study is to analyze the use of incentives for rebalancing in BSSs. Keeping this goal in mind and not losing track, research questions are formulated, which will be answered in the conclusion of this thesis.

The first research question builds the basis of this thesis, which are reallocation techniques in BSS:

Which reallocation methods exist for BSSs?

As this paper focuses on agent-based reallocation methods, it is of substantial importance if users would respond to incentives offered. This is because their willingness to pursue the suggestions is a presumption for agent-based reallocation techniques. In order to keep this in mind, research question 2 is formed as follows:

Would users respond to incentives for changing their target location?

In contrast to the first research question, which focuses on the underlying topic's theory, the third research question aims for practical implications. In order to implement incentives in BSSs successfully, it is important to know which ones are most effective. Therefore, the last question which should be answered in this thesis states:

Which incentive(s) would be most effective for agent-based reallocation?

Through these research questions, the theoretical as well as practical part of the topic are covered. Furthermore, the essential presumption for the focus of the work is included by the second research question.

In this chapter the overall topic was introduced to give the reader an overview of what to expect. First, the seven chapters, which form this master thesis, were explained. Afterwards, an introduction to bicycle-sharing systems and important definitions of the topic were given. The last part of this chapter dealt with the problem approached. In line with this, the three research questions were drawn to substantiate the problem and to keep the goal in mind. The next chapter helps to answer the first research question by explaining operator-based reallocation methods.

2. Operator-based reallocation methods in PBS

In the following chapter operator-based reallocation methods discussed in the literature will be listed and shortly explained. Operator-based rebalancing is conducted by the system's staff. Mostly, trucks are employed to move bikes from one station to another. Through this redistribution the performance of the program should be maintained and enhanced.

Operator-based reallocation methods are divided into static and dynamic ones. As already mentioned, in case of static reallocation methods of PBS customer demand is assumed to be negligible. Hence, a situation in which (almost) no demand takes place, is considered. Such a situation could be at night, when it is assumed that demand is mainly connected to daylight. In contrast to static methods, dynamic models do not neglect demand. Hence, balancing of PBS is done during peak hours (Contardo et al. 2012, p. 3).

First, attention will be given to static methods. In this subchapter the problem addressed – the calculation of thresholds and efficient routes for trucks as well as a simulation program and a comparison of distinct static methods – is pointed out. Second, dynamic methods divided into models, simulations and decision support systems will be subject to discussion.

2.1. Static methods

One objective of static methods is to schedule vehicle routes to visit the stations in minimum possible time to accomplish a certain target. This target may be a desired number of bikes present at each station (Contardo et al. 2012, p. 2). Other goals are to find lower and upper bounds and to be able to calculate the optimal inventory size to serve near future demand.

An argumentation for static solutions in PBS is that regulation approaches are mostly conducted during night-time and that some operators even close their PBS in this time to conduct rebalancing activities (Chemla et al. 2012, p. 1).

Solution techniques may be based on enumeration, cone generation and the development of a stochastic, mixed-integer program to generate partial redistribution plans in circumstances when demand outstrips supply. The purpose of these solutions is to correct short term demand asymmetry (Miller-Hooks and Nair 2010, p. 2). Another solution approach is to take the allowance of advance reservations into consideration. In this case the uncertain demand becomes a known component. Hence, this static portion can be guaranteed to be served (Miller-Hooks and Nair 2010, p. 25).

2.1.1. Static rebalancing problem definition

In order to find appropriate static methods as solutions for unbalanced BSSs, existent problem definitions in literature are adapted to address the problem at hand. For the static case, in which no bike is moving and only a unique truck is considered, a swapping problem for any capacity and only one type of items emerges (Benchimol et al. 2011, p. 39), hence, the traveling salesperson problem can be taken into consideration (Benchimol et al. 2011, p. 44). Additionally, due to the calculated optimal number of bikes at each station, which is tried to be reached with a regulation system consisting of a fleet of vehicles, the problem pointed out can also be categorized as a *Single Vehicle One-commodity Capacitated Pickup and Delivery Problem*. This problem is faced if the number of moving bikes is negligible (static case) and if the region is divided into districts (Chemla et al. 2012, p. 1). Furthermore, the routing problem can be defined as a variation of the pickup and delivery problem (Raviv and Kolka 2013, p. 1078), while the inventory problem may be classified as a closed-loop inventory problem (Raviv and Kolka 2013, p. 1078).

Additionally, the problem tackled in this thesis can be divided into a non-pre-emptive and pre-emptive one. The latter describes that the bikes "can be dropped at temporary locations along the route before being moved to their final destination" (Benchimol et al. 2011, p. 39), while in the former case this is not possible (Benchimol et al. 2011, p. 42, p. 57).

As mentioned above, when using a dedicated fleet of trucks for balancing bicycle-sharing schemes, decisions regarding the routes, that the vehicles should follow, and the number of bicycles, that should be removed or placed at each station on each visit, are problematic (Raviv et al. 2013, p. 187). Providing efficient, cost-effective operational strategies for fleet management leads to the goal of finding a fleet redistribution plan at lowest possible cost through which most near future demand scenarios are satisfied (Miller-Hooks and Nair 2010, p. 3).

2.1.2. Finding upper/lower boundaries of the optimal solution

To find a good lower bound of the optimal solution, an integer program with an exponential number of constraints may be solved by a brand– and- cut algorithm. Furthermore, the problem is shown to be non-deterministic-hard which helps to detect whether there is an optimal solution for the same cost (Chemla et al. 2012, p. 3). Moreover, a tabu search may be done. A tabu search allows non-improving moves, while a tabu list is updated with every move to prevent from cycling. Additionally, a stopping criterion has to be identified (Chemla et al. 2012, pp. 14). In the underlying case this means that vertices are either added to or removed from a predefined subset. However, they are saved in a tabu list and, hence, are not “used for a given number of iterations. If the procedure finds a violated capacity constraint, it is added to the linear program” (Chemla et al. 2012, p. 13).

The results show that the gap between the best upper bound and the best lower bound is with an average of less than 5% rather small. Furthermore, Chemla et al. (2012) found that the local search (balancing the system in districts separately) is very efficient for instances up to 60 vertices. For larger ones the local search becomes less effective (Chemla et al. 2012, p. 20). This might be a consequence of the size of the neighbourhood. If the neighbouring district is rather large the vehicle has to make numerous visits at some vertices. Furthermore, the smaller the capacity, the harder is the problem to solve (Chemla et al. 2012, p. 22).

Powell and Carvalho (1997) used a flexible, fast solution approach to solve the integer, multicommodity network flow problems. In their numerical experiments on average an optimality gap of 3.5 % between the upper and lower optimal boundaries was found. This might be due to relaxations in bounds and optimal values as well as due to the coordinate search used to update the upper bounds. (Powell and Carvalho 1997, p. 539)

Lower bounds, approximation algorithms and a polynomial algorithm were also created by Benchimol et al. (2011). They employed an integer linear programming approach to develop lower boundaries for the problem at hand (Benchimol et al. 2011, p. 40).

2.1.3. Simulations

Additionally to all these approaches to solve the static repositioning problems, Caggiani and Ottomanelli (2013) created a bike sharing system simulator in which static rebalancing is conducted by pick-up or open trailers. In their simulator an operating day is divided into discrete time intervals and the number of bikes to be picked up is given. It was assumed that each bike request, which had not been satisfied, would turn users away as well as full stations create undesired waiting time for users. Before each time interval the system could be rebalanced. (Caggiani and Ottomanelli 2013, p. 205)

The model simulated the destination choice in order to be able to predict the arrival time for each user. The choice model described was based on relative demand and the nature of the trip, whether it was a one-way or round trip. Based on this simulation a decision support system was created. (Caggiani and Ottomanelli 2013, p. 205)

Shu et al. (2013) worked on the development of models, which predict the utilization rate of bicycles in public sharing-systems. Especially, the effects of deployment and redistribution on the utilization rate of PBS were emphasized (Shu et al. 2013, p. 4). For this purpose they created a simulation model.

The starting situation was that an initial allocation of bikes at each station was given. Users were assumed to arrive randomly at the station and rent the bikes (Shu et al. 2013, p. 5). It has to be highlighted that bicycles were allocated to customers on a first come first serve (FCFS) basis. Therefore, if the resource of available bikes was exhausted, late-comers were not able to rent a bike (Shu et al. 2013, p. 6).

The desired utilization rate of the system was fixed and, hence the optimal initial allotment was calculated and also applied at each station at the beginning of each planning period. The simulation was run 100 times for each desired utilization rate to evaluate the performance of the system and, furthermore, to get the sample average of it. For each simulation the direct time-expanded network was used and the number of customers arriving at a station in each time slice of 15 minutes was assumed. The simulation had been run for one week to get a valuable number of trips in the system. From this the bicycle utilization rate is calculated. (Shu et al. 2013, p. 15)

By implicitly assuming that rebalancing of the system was performed at the end of each day, it was found that less docks at each station were needed (Shu et al. 2013, p. 21). As redistributions were time-consuming and costly, further tests were made. It was found that if the number of bikes in the PBS exceeded 30.000, several daily redistributions were sufficient. This was owed to the outcome that more frequent rebalancing actions would not enhance the performance of the system substantially in contrast to a small amount by day (Shu et al. 2013, p. 22).

2.1.4. Fleet management and its effect on rebalancing

In the literature the possible effect of the initial allocation and number of bicycles in the system on the need of rebalancing has been often discussed. Schuijbroek et al. (2013) stated that “the service level requirements can be met when the inventory is between a lower and upper bound” (Schuijbroek et al. 2013, p. 2). Hence, an optimal inventory at the beginning of a certain period may be sufficient to satisfy short-term demand. Furthermore, they assumed that some stations may be self-sufficient due to an equal push and pull demand. Therefore, these stations do not have to be rebalanced. (Schuijbroek et al. 2013)

In contrast, the objective of a study by Fricker et al. (2012) was to examine inhomogeneous systems. An inhomogeneous system was understood as a system with very different arrival rates and destinations, hence, a system which was not self-sufficient. They claimed that the system consists of clusters. While in the case of homogenous stations the optimal fleet size is slightly more than the half of capacity, the optimal capacity of inhomogeneous stations depends on its cluster. Therefore, each cluster has its own ratio of problematic stations. Although this ratio can be kept small in some clusters, the performance of the overall system may still be bad due to the ratios of the other ones. Fricker et al. (2012) conclude that the performance of inhomogeneous systems collapses due to heterogeneity. Not only of heterogeneity between stations, but also among clusters. (Fricker et al. 2012, p. 266)

The problem of an optimal number of bicycles, their locations and the number of bicycle docks in each station can also be solved for any given demand. These factors influence substantially the bicycle utilization rate as well as the number of trips made (Shu et al. 2010, pp. 6). To analyse and estimate the number of trips, with a given initial allotment of bicycles and arrival demand, which can be supported in the system, a stochastic network flow model is created by Shu et al. (2010). Their approach considers that an effective redistribution may reduce the needed number of docks in a station (Shu et al. 2010, p. 7).

However, one of their later results indicates that there is a limit to the amount of useful bicycles. Hence, beyond the optimal number of bicycles in the system, further bikes do not improve the performance of the system (Shu et al. 2013, p. 12). Moreover, Shu et al. (2010) came to the conclusion that an optimal allocation at the beginning of the week has only limited influence on the performance of the system. The system will be unbalanced quickly due to the actual arrivals and utilization requirements of the passengers. Hence, a time period of one week is too long for an initial optimal allocation to be sufficient for a long-lasting good performance (Shu et al. 2010, pp. 22).

Rebalancing helps to improve the performance of the system, also compared to a random allocation of bikes. The influence is greater in a system with a moderate utilization rate than in systems with very high or low utilization rates. This is because in the latter cases the bicycles are most of the time under demand or useless, which makes static repositioning ineffective (Shu et al. 2010, p. 26). Furthermore, Shu et al. (2010) found the improvement owing to the redistribution (in terms of the number of ridership supported) to be around 15% to 20% in a system with a moderate utilization rate (Shu et al. 2010, p. 27). Therefore, finding capable rebalancing techniques and efficient routes for balancing vehicles is a main goal of operators.

2.1.5. Solving the routing problem

As static operator-based reallocation techniques neglect user demands and are mostly conducted by trucks in BSSs, the efficient routing of the balancing vehicles is a main goal. Likewise, the aim of a study by Benchimol et al. (2011) was to find a minimal route for the trucks that balance the system. “The stations have to keep a good ratio between the total number of places and the number of bikes in each station” (Benchimol et al. 2011, p. 38). The maintaining of this ratio is called balancing of the stations. In this paper it is assumed that no bike is moving and that there is a unique truck (Benchimol et al. 2011, p. 38). Therefore, the Chalasani-Motwani algorithm, which encountered the C-delivery traveling salesperson problem (Benchimol et al. 2011, p. 44), is adapted to a situation when “the capacity is not counted in unary basis, but instead when the input is a list of numbers” (Benchimol et al. 2011, p. 40). The Chalasani-Motani approach is adapted to get a 9.5-approximation algorithm for an optimal balancing tour that works in a polynomial time for a situation when the truck starts and finishes at the same station (Benchimol et al. 2011, p. 43).

Likewise, in a pre-emptive model of Chemla et al. (2012) the routing problem is approached with the employment of only one truck. Although their model includes several trucks, the region is divided into districts and “each district is covered by a single truck that has to redistribute the bikes in order to respond to the morning peak at best” (Chemla et al. 2012, p. 1). The authors focus on the reallocation process in each district separately, hence, it can be said that also a single vehicle is considered in the model (Chemla et al. 2012, p. 1). The aim is to find the minimal cost route, while drops and multiple visits of the bikes are allowed (Chemla et al. 2012, p. 2). The model is based on the presumption that an upper boundary for the number of visits the truck has at a certain station is given for any optimal solution (Chemla et al. 2012, p. 7).

2.1.6. Effect of inventory size and repositioning time on number of shortage events

The problems mentioned are not only hard to solve, but it is also difficult to evaluate the effect of inventory size and repositioning time. Hence, Raviv et al. (2013) compared an arc-indexed formulation with a two-phase arc-indexed formulation through a numerical study based on the BSS of Vélib (Raviv et al. 2013, p. 187).

In their study user dissatisfaction with the system is measured through the expected number of shortage events (full/ empty stations). The costs, resulting from the users' dissatisfaction with the system, and the operating costs, caused by the repositioning trucks, form the total costs of the problem. A presumption is made that a depot with a relatively large capacity, large inventory and no demand is at the starting as well as ending point of each vehicle's route. (Raviv et al. 2013, p. 193)

Since the aim is to minimize the overall costs in the system, the trucks may redistribute bicycles in the system in any way that fits to this goal. Hence, bikes may be brought to a station which has already its ideal quantity, but the received bikes are from a station where their presence are more costly (Raviv et al. 2013, p. 198). The results of the numerical study show that the number of shortage events have been negatively affected by the number of stations and vehicles. In contrast, the influence of the length of the repositioning time is very small (Raviv et al. 2013, p. 212).

Furthermore, the results highlight that even if the inventory levels are set to their optimal values, approximately two-thirds of the lost sales still occur. The reason for this is that the demand for bikes or free docks is too different at some hours of a day, that this gap cannot be closed by initial allocation (Raviv et al. 2013, p. 221). Therefore, dynamic methods are proven to be important. These will be explained in the next subchapter.

2.2. Dynamic methods

Operator-based dynamic methods have received great attention in research. Lots of studies have focused on different approaches to make operator-based dynamic reallocation techniques most efficient. Studies have been conducted to develop a variety of models to optimize the network flow problem, to minimize costs resulting of reallocation activities as well as of user dissatisfaction.

The problem of moving bicycles during rebalancing actions is added to the static one. Hence, similar as well as completely different approaches are taken. In contrast to static methods, emphasize is put on decision-support systems, performance measures and forecasting methods to make dynamic reallocation efficient. Hence, in the following subchapter the existing literature and solution approaches are categorized into performance measures, simulations, decision-support systems and forecasting methods.

2.2.1. Problem definition of dynamic methods

The main problem in dynamic reallocation techniques is to determine when they are needed. If they are conducted too early, they might not have been necessary as the system would have balanced itself. However, if they are started too late, the performance of the system suffers. For this reason a lot of studies have focused on creating appropriate lower and upper vehicle inventory thresholds, which signal the operator to start rebalancing techniques (Kek, et al. 2009, p. 150; Papanikolaou 2011, p. 128; Contardo et al. 2012; Schuijbroek et al. 2013, p. 2).

Likewise to inventory thresholds, performance measures for the system are essential to be created. While inventory thresholds merely focus on the fleet size in the stations, performance measures also take other factors of the system into consideration for determining the point of time, when rebalancing should be conducted. (Barth et al. 2001, p. 1219)

In general the problem pointed out can be classified as a multicommodity network flow problem. In other words this presents a fleet management problem for a dynamic system with multiple vehicles and limited substitution (Powell and Carvalho 1997, p. 522). Furthermore, the problem of inhomogeneous systems is employed in this context (Fricker et al. 2012, p. 365).

Likewise to static methods, the optimal repositioning flow, distribution patterns and routing are also problems of the dynamic techniques (Caggiani and Ottomanelli 2013; Schuijbroek et al. 2013, p. 2). Hence, *Bike Sharing Pickup and Delivery Problem* is also a problem involved in dynamic reallocation methods (Caggiani and Ottomanelli 2013, p. 204). However, it might be even more complex as current user demand has also to be considered in solving these problems.

2.2.2. Performance measures and thresholds for the system

Barth, Han and Todd (2001) examined a real-world shared (electric) vehicle system operating on the University of California-Riverside campus to determine the point of time when dynamic vehicle relocation actions are necessary. For this, the authors created performance measures for multi-station shared vehicle systems. (Barth et al. 2001, p. 1219)

A common performance measure it the percent usage time of each vehicle, which is calculated by dividing the time a certain vehicle is in use by the operating time of the system. This can be done for all bikes in the system, which gives an overall usage time and performance indicator for the whole system. (Barth et al. 2001, p. 1220)

The average time spent by a user to rent a vehicle, is another essential performance measure of the system. This time period includes the registration and waiting time. A further measure is the imbalance of the system. Meaning if there are full or empty stations. (Barth et al. 2001, p. 1220)

In order to help operators to evaluate when to conduct reallocation activities a simple threshold may be used. Thresholds are good indicators to evaluate the performance of the system. They can be quantitatively calculated by summing up the total area under the threshold curve of a day's overall system performance. (Barth et al. 2001, p. 1222)

A paper by Raviv and Kolka (2013) introduced a user dissatisfaction function as well as a dynamic inventory model and its function to provide an efficient and accurate approximation method to estimate the performance of a station (Raviv and Kolka 2013, p. 1079). Another solution to improve the performance of BSSs is to use simulations.

2.2.3. Simulations

In the following simulations in the context of dynamic reallocation techniques are listed. For example, Contardo, Morency and Rousseau (2012) developed a simulation model for PBS reallocation techniques to schedule possible vehicle routes. The aim is to minimize shortfalls. The vehicles visit the necessary stations to pick up bikes or deliver them. In their simulation a number of stations, fleet size of rebalancing vehicles and time-dependent demand for bicycles are given. (Contardo et al. 2012, p. 1)

Moreover, the creation of the simulation was carried by the idea to test the sensitivity of algorithms to the granularity of time discretization. A set of 120 instances with different numbers of stations (25, 50, 100) was generated. In addition, time horizons of two hours and 24 periods of five minutes each and 60 periods of two minutes each were included. (Contardo et al. 2012, pp. 13)

They found that for the smallest set of instances which consists of 25 stations, 24 periods and five minutes the arc-flow formulation produced better lower and upper boundaries than their mathematic formulation. However, their mathematic formulation performed better for the larger instances. (Contardo et al. 2012, p. 15)

Furthermore, a randomly assigned system was compared with a system consisting of clusters. Meaning, in the former one the stations are randomly distributed to be of a push or pull nature. Contrastingly, in the latter kind clusters are existent. The stations in one cluster have the same nature regarding pull or push demand. “The results show that the clustered instances are more rigid, in the sense that they usually accept worse solutions than the random instances do, but the lower bounds are stronger” (Contardo et al. 2012, p. 15).

A simulation model by Köchel, Kunze and Nieländer (2003) also tries to optimize the performance of PBS. The variables, which are tried to be optimized, are fleet size, the number of vehicles in the system and the reallocation policy (Köchel et al. 2003, p. 445). First, simulations are used to determine the optimal fleet size without any reallocation policies. Then, situation-dependent reallocation policies are added. Situation-dependent means that rebalancing actions are triggered when a location has too many or a shortage of vehicles (Köchel et al. 2003, pp. 453).

Their simulation is based on the assumption that no bikes break down or are involved in accidents. Hence, the fleet size is kept constant. Furthermore, “capital costs of holding a vehicle in the system are included in the gain from vehicle renting and in the waiting cost for a free vehicle“ (Köchel et al. 2003, p. 455).

Another simulation model for dynamic bikes redistribution process was created by Caggiani and Ottomanelli (2013), which is aimed to minimize the vehicles repositioning costs for operators of PBS. The model determines the “optimal repositioning flows, distribution patterns and time intervals between relocation operations by explicitly considering the route choice for trucks among the stations” (Caggiani and Ottomanelli 2013, p. 203).

In contrast, the model by Papanikolaou (2011) evaluates the effect of asymmetric demand patterns by simulating different scenarios. For this purpose threshold boundaries are set and their changes in time are described (Papanikolaou 2011, p. 128). If users enter the system at a full station, they wait for some time and then exit the system. If users, who have already rented a vehicle, do not find an available parking place, they drive to the closest available station. The capacity of the system depends on the average trip time, pick-up time and fleet size. Demand patterns are the time-based pick-up and drop-off requests in the system. It is supposed that the system starts in an optimum equilibrium. This is defined by a demand pattern in which each outgoing trip is balanced by an incoming trip. Hence, the inventory levels remain stable (Papanikolaou 2011, p. 129). With a change of demand pattern a disequilibrium is created, this can be changed by a further alteration of the demand pattern. Results show that the more asymmetric demand patterns are implemented the longer is the trip time in the system (Papanikolaou 2011, pp. 130).

2.2.4. Decision support systems

If user demands are not met, dissatisfaction among users and a potential loss of revenues among the operators are caused. Hence, decision support systems are developed to help operators to minimize the costs resulting of unsatisfied customers in BSSs.

A novel three-phase decision support system developed by Kek et al. (2009) shall help operators to evaluate the different relocation strategies, manpower and operating parameters. The three phases are optimizer, trend filter and relocation simulator. While the first phase gives the allocation of the resources with the lowest costs, the trend filter recommends operating procedures and parameters and the last phase evaluates the improvements in the system (Kek et al. 2009, p. 151). In practice, the operator sets upper and lower thresholds for the inventory of the stations. If the upper threshold is reached or exaggerated, the system prompts the operator to move bikes off the station. On the opposite, if the lower threshold is met, the operator is asked to move bikes to the station. This decision-support system may also be used for user-based vehicle relocation techniques (Kek et al. 2009, p. 150). Although the decision support system was developed for carsharing systems, it may be adapted to PBS.

Furthermore, a decision support system by Caggiani and Ottomanelli (2013) is aimed to minimize the total costs for the operator resulting from reallocation and lost users. Lost consumers are caused by unsatisfied conditions due to empty or full stations in the system (Caggiani and Ottomanelli 2013, p. 207). The decision support system “leads to a reduction of the number of lost users. Also in the case of low demand level, positive results have been reached. Assuming higher level of demand, due to the congestion of the system, the proposed method shows a lower reduced number of lost users” (Caggiani and Ottomanelli 2012, p. 208).

The results of a numerical application for three different levels of demand and different days of the week show that constant relocation time intervals perform better in cases of low demand, while higher demand cases are better served with a fuzzy decision support system. (Caggiani and Ottomanelli 2013, pp. 207)

2.2.5. Forecasting

The decision support system of Caggiani and Ottomanelli (2013) is based on a forecasting module that estimates incoming and leaving bikes in each dock. Their forecasting model is based on historical time series collected by the usage monitoring systems (Caggiani and Ottomanelli 2013, p. 205). There are also other ways to forecast demand than use historical data. A good forecast helps to calculate the optimal fleet size, find ideal inventory allocation and most effective repositioning technique. Hence, several studies, at least partly, dealt with the problem of making appropriate forecasts.

A way of forecasting demand was introduced by Rudloff and Lackner (2013). The aim of their study was to develop a count model for modelling bike sharing demand and not only to rely on historic data. This helps to improve the rebalancing of the system. They compared models based on count models, Negative Binomial and hurdle models "While it turned out that the hurdle model works best in modelling the demand of bike sharing stations, these models are complex and might not be ideal for optimization procedures" (Rudloff and Lackner 2013, p. 16).

Likewise, Borgnat et al. (2009) created a statistical model to describe the daily and weekly demand patterns of the system. For this purpose, they analysed the Velov bicycle program and employed a combination of non-stationarity and cyclo-stationarity methods. The model may predict the number of rentals per hour based on the number of bikes and subscribers and external conditions like weather. (Borgnat et al. 2009, p. 6)

Raviv and Kolka (2013) had a complete distinct approach to forecast the demand of the stations. They aimed to close the gap in the literature which does not capture the minute-to-minute dynamics of a station and assumed that replenishment operations by new and returning bikes occur periodically. Their argumentation is based on the presumptions that replenishment by returned bikes happens more often than replenishment by new ones. (Raviv and Kolka 2013, p. 1079)

Furthermore, the interdependences of the distinct demand patterns at neighbouring stations as well as the effect of alternative origin stations on the arrival process of returners at destination stations are taken into consideration. These interdependences are based on two assumptions. First, it is assumed that unsatisfied renters and returners are likely to seek service in neighbouring stations. Second, if a customer decides to leave the system at a certain station due to its emptiness, she/he will never return a bike at the presumed end-station. (Raviv and Kolka 2013, p. 1083)

This chapter was written to give answer to the first research question. The problems and approaches of operator-based reallocation techniques were described. First, different ways to find upper and lower boundaries and to solve the routing problem in static rebalancing were listed. Furthermore, the effect of fleet management, inventory size and repositioning time on the performance of systems was discussed. Likewise, simulations, which try to enhance the BSSs' performance, were explained in the static reallocation theory subchapter.

Similarly, simulations of dynamic reallocation techniques were given in the second subchapter, which dealt with dynamic rebalancing actions, of this chapter. Moreover, forecasting methods and decision support systems were named. Some of the dynamic models and simulations were further processed and incentives were included. These are explained in the next chapter dealing with agent-based reallocation techniques, which form the second part to the answer of the first research question.

3. Agent-based reallocation methods in PBS

In case of agent-based models, the rebalancing activity is shifted from trucks or employees to the users of the PBS. Strictly speaking agent-based methods might be seen as a subcategory of dynamic ones, as the reallocation still happens while the system is in use.

User-based relocation strategies have environmental advantages, as no additional vehicle trips are needed (Weikl and Bogenberger 2012, p. 356). In case of public bike sharing systems the main approaches are to rebalance by motivating users to go to a determined end-station (Chemla et al. 2013) or to eliminate trips, which are not favourable for the overall system's performance (Waserhole et al. 2012a).

To solve the problem of one-way rentals through pricing, hence, user-based, is already known for trucks and cars (Waserhole and Jost 2012, p. 3). For shared-use car systems trip joining like ridesharing and trip splitting are options (Barth et al. 2004, p. 1). However, as in the following only PBS will be part of the analysis, some major differences to shared-use car systems have to be kept in mind (Waserhole and Jost 2012, p. 3).

Vehicle rental systems usually operate on a daily or hourly basis, while BSSs often function on a minute basis. Hence, renting is conducted with a possible high intensity in PBS. Furthermore, the large majority of bike rentals are for one way, while cars are usually taken for round trips. Additionally, vehicles are usually reserved in advance when rented through vehicle rental systems. In comparison, hardly any PBS offer reservations. (Waserhole and Jost 2012, p. 3)

Due to all these factors, which increase an unbalancing of the system, the agents need to be motivated to rebalance the system. Hence, different kinds of incentives are implemented in these agent-based methods. In existent literature they are presented by power of two choices and pricing techniques. Furthermore, pricing techniques can be employed to alter the end station decision of approached users or to alter their total trip decision. In this chapter, first the power of two choices will be explained. Afterwards the two ways of employing pricing methods are discussed.

3.1. Power of two choices

Fricker and Gast (2014) elaborated two studies on the performance of BSSs. They developed a model of a BSS and analyzed on its basis the performance in terms of problematic stations. Problematic stations are the ones, which cannot serve users' demand, hence, are full or empty.

First, the difference in performance, when employing agent- or operator-based redistribution mechanisms, is analyzed and discussed. Secondly, these redistribution methods are compared for symmetric and asymmetric systems. (Fricker and Gast 2014)

As mentioned, Fricker and Gast (2014) created a model of a BSS, in which the arrival and departure of users at each station are modelled as stochastic processes (Fricker and Gast 2014, p. 2). The underlying system consists of numerous stations and each has its capacity *K*. A homogeneous system is first discussed, meaning that the flow of bicycles between two stations is, on average, the same in both directions. Based on this model the performance is measured, which is influenced by the random demand of the users. The impact of station capacity as well as of operator- and agent-based reallocation techniques on the system's performance is measured (Fricker and Gast 2014, p. 3).

It is found that the proportion of problematic stations decreases as the capacity *K* grows. The optimal fleet size in order to minimize the number of problematic stations is given in the following equation. (Fricker and Gast 2014, p. 3)

$$\text{optimal fleet size} = \frac{\mathrm{K}}{2} + \frac{\Lambda}{\mu} \qquad (1)$$

K is the capacity of the stations, Λ is the arrival rate of users at a station and $\frac{1}{\mu}$ presents the average trip time. Hence, the optimal fleet size is half the capacity plus the demand in the system (Fricker and Gast 2014, p. 3).

Furthermore, a Markovian model is considered. The stations are grouped in clusters, which are connected to a certain location or level of popularity. All stations in the same cluster have the same characteristics. If a user is not able to rent a bike due to a lack of availability, she/he leaves the system. When the user wants to return the bike and the destination station is saturated, she/he looks for another station in the same cluster, the process is repeated until a free dock is found (Fricker and Gast 2014, p. 4). First, only one cluster system is considered.

A limiting proportion of problematic stations is the goal in this study. For this, a saturated station, in case of a user wanting to return a bike, is seen as more problematic than an empty station, in case of a user willing to rent a bike. This is because in the latter case the user is able to simply leave the system. (Fricker and Gast 2014, pp. 6)

It is proved that an equilibrium point is existent (Fricker and Gast 2014, p. 7). Hence, an optimal proportion of bikes per station can be found (Fricker and Gast 2014, p. 9). However, "even for a symmetric system for which the number of bikes per station is chosen knowing all parameters of the users, the proportion of problematic stations only decreases at rate" (Fricker and Gast 2014, p. 10) one divided by the capacity of the station. Therefore, if stations in a system have capacities of 30 vehicles the performance is almost equal to capacities of 10 to 20, but as soon as the capacities are higher or lower, the performance of the system decreases substantially. However, if the capacity is set at 100, the performance is less sensitive to the capacity and a little better (Fricker and Gast 2014, p. 11). This leads to the result of Fricker and Gast (2014) that even symmetric systems are subject to poor performance if no rebalancing techniques are employed (Fricker and Gast 2014, p. 10).

When trucks are used for rebalancing, the performance is increased substantially if the rate at which the trucks visit the stations is 10% of the arrival rate of customers. In this case, trucks choose two stations at random and equalize their numbers. The traveling time of a truck equals the traveling time of users as loading takes time. The marginal improvement of the balancing trucks decreases quickly. Hence, the need for trucks to rebalance the system is rapidly saturated. (Fricker and Gast 2014, p. 19)

When implementing in the system that users are aware of saturated and empty stations, it is shown that "although forcing people to go to a non-saturated or non-empty station reduces the unhappy users since everyone can take or leave a bike at any time, it makes the system more congested and does not improve the overall performance" (Fricker and Gast 2014, p. 14).

Through implementing the power of two choices in the system the user gets the possibility to choose two stations as destination, when renting a bike, and is pursued to go to the emptier one (Fricker and Gast 2014, pp. 14). An incentive may be added to pursue users to choose the station, which improves the performance of the system. The results show that the situation enhances substantially, if users return the bicycles at the emptier one of two station. This improvement can also be seen, if only a fraction of users does it (Fricker and Gast 2014, p. 3). Precisely, it is shown that the performance of the system is substantially improved by implementing such a reward, even if only 20% follow it (Fricker and Gast 2014, p. 16).

When taking again a station's capacity of 30, the proportion of problematic stations was at best around 7% before implying an incentive scheme. By introducing an incentive the proportions can fall to 10^{-6}. Furthermore, the performance is less sensitive to changes of the number of vehicles. (Fricker and Gast 2014, p. 16)

3.1.1. Comparison of operator- and agent-based reallocation methods

For the comparison of operator- and agent-based rebalancing methods, the redistribution rate, which is the ratio of the number of bikes that have to be moved by trucks over the number of bikes that are taken by users, is calculated. The redistribution rate may optimize the performance and depends on the fleet size and the station capacity (Fricker and Gast 2014, p. 4). It is found that the minimal redistribution rate, needed to suppress any problematic station, decreases at the inverse of the station capacity (Fricker and Gast 2014, p. 17).

It is shown that a combination of trucks and the two-choice incentive method results in an optimal redistribution rate (Fricker and Gast 2014, p. 21). Therefore, both reallocation techniques are needed to receive the best result possible.

It has to be kept in mind that these analyses are based on a completely symmetric system. Even in this case the results show that a BSS will always have poor performance without any rebalancing techniques. Hence, it may be suggested that the situation does not get better if preferred areas, hence, asymmetry is added to the system, which will be analysed in the following. (Fricker and Gast 2014, p. 10)

3.1.2. Comparison of the power of two choices in asymmetric and symmetric cities

In practice, cities are usually asymmetric, which means that certain stations have higher demand than others. Therefore, two different clusters are implemented to compare the operator-based reallocation technique with an agent-based one for homogeneous and inhomogeneous systems. (Fricker and Gast 2014, p. 17). When a user enters the system, she/he rents a bike in one cluster. With a probability of one half the user drives to the other cluster or stays in the first one. If the user arrives at a full station, she/he stays in the current cluster and looks there for a non-saturated station (Fricker and Gast 2014, p. 17).

While the performance of a symmetric system is optimal if the bikes per station is a little more than half of the available spaces (like shown in equation 1), in the asymmetric case the number of vehicles should be smaller. “If the number of bikes is optimal, a user going from an under-loaded to an overloaded station has more than 25% chance of not finding a bike and more than 10% of finding a saturated station” (Fricker and Gast 2014, p. 18). Furthermore, in an under-loaded area the proportion of full stations is always small. However, this is not true, if the numerous bikes are implemented in the under loaded area (Fricker and Gast 2014, p. 17). As a result, asymmetry without any regulation leads to poor performance, even if the system is close to symmetry (Fricker and Gast 2014, p. 18).

In case of a symmetric situation the two choices rule outperforms the truck rebalancing in terms of system performance by far. However, when it comes to asymmetric situations the two choices rule does not result in a good performance. “The case where all the users obey the two choices rule improves the situation with or without regulation” (Fricker and Gast 2014, p. 20). In this case, regulation means rebalancing by trucks. However, if the number of trucks is low the incentive scheme is not sufficient to reach good performance, even if all users follow the two choices rule. “These results show a mechanism to balance the number of bikes between clusters is necessary to achieve a good performance. This mechanism can be a regulation mechanism […] but it can be incentives: users get a reward if they return their bikes in a station with a high elevation. But the later, very interesting for a symmetric model, performs badly in presence of asymmetry” (Fricker and Gast 2014, p. 20).

Such a reward might be price incentives, which are discussed in the following subchapters.

3.2. Price incentives employed in end-station decision

Real-time pricing mechanism are common control mechanism in transportation or car-rental industry. Hence, it might be a solution for user-based rebalancing in PBS (Fricker and Gast 2014, p. 2). Trips to certain stations, which are undersupplied, can be offered for a very cheap price or even for free. The specials could be communicated via mails, social media or at rental at the starting dock (Weikl and Bogenberger 2013, p. 102).

There are different models using price incentives to motivate users to change their end station. This price incentive approach will be explained in line with the models created by Pfrommer et al. (2013) and Chemla et al. (2013).

First, the dynamic vehicle redistribution model by Pfrommer et al. (2013) will be explained. They implemented price incentives in their simulation of a shared mobility system. At the end the reallocation techniques with trucks and with price incentives as well as a combination of them are compared.

Their model parameters consist of a set *S* which represents all stations, the time *t* is discrete and indexed on a one-minute level. T_{hist} shows all observed time steps so far. It is separated between workdays and weekend, which can be seen through the variable *w*. Every day is divided into 72 parts k of 20 minutes. All users' departures and arrivals are summed up in matrices of |S| x |S|, moreover, the sum of departing customers going from station a to b in a timeslice k and on a day w is $DEP_{a,b}(k,w)$ (Pfrommer et al. 2013, p. 5). The same is valid for the sum of arrivals from two stations $A_{a,b}(k,w)$. Therefore, the average number of arrivals (Λ, at the stations a and b) and of departures (M, at the stations a and b) at time t can be expressed as (Pfrommer et al. 2013, p. 5):

(2) $$M_{a,b}(t) = \frac{DEP_{a,b}(k(t),w(t))}{|\{t' \in T_{hist} :\ k(t')=k(t),\ \ w(t') = w(t)\}|}$$

(3) $$\Lambda_{a,b}(t) = \frac{A_{a,b}(k(t),\ \ w(t))}{|\{t' \ \in T_{hist} : k(t') = k(t),\ \ w(t')=w(t)\}|}$$

For the purpose of stimulating the system, several assumptions about the customers' behaviour were made. First, potential users, who do not get a bicycle immediately, do not wait for one to return or visit another docks, but leave the station unsatisfied. Any travel time between any two docks equals the average travel time calculated from the historical data. If a customer wants to give a bicycle back but arrives at a full station, he or she will try the next station, but won't come back to the initial one or waits. (Pfrommer et al. 2013, p. 6)

In the following, it is assumed that each user values the additional time, if accepting an incentive, in money. Furthermore, the assumption that the final destination is at the centre of mass of the Voronii region, "which is the polytope that contains all points closer to a given station than to any other" (Pfrommer et al. 2013, p. 6), is made.

Incentives are offered upon arrival at the full station, and customers are able to evaluate the value of the incentive against their additional effort. The "marginal cost of travel c for each arriving customer is drawn from a uniform distribution" (Pfrommer et al. 2013, p. 7), while c_{max}= £20/km. Naturally, the user chooses the best offer and tries to achieve maximum value, hence, the maximum amount of money offered minus the distance times the marginal cost. Always the best incentive is chosen, provided that its value exceeds zero. Hence, also the best incentive has to provide a positive value to be selected (Pfrommer et al. 2013, p. 7). All this is based on the assumption that arrivals and departures are deterministic (Pfrommer et al. 2013, p. 8).

3.2.1. Comparison of operator- and agent-based reallocation methods

In the following, a Monte-Carlo simulation is used to compare the two balancing approaches, trucks and incentives (Pfrommer et al. 2013, p. 23). The comparison of distinct numbers of trucks and levels of price incentives is based on the service level. The service level is defined by the number of potential customers minus the number of no-service events divided by the number of potential customers (Pfrommer et al. 2013, p. 24). “The number of total no-service events is the sum of customers who could not rent a bike at an empty station and customers who wanted to return their bike at a full station” (Pfrommer et al. 2013, p. 24).

The results show that a higher number of trucks as well as bigger incentives have a positive effect on the service level. However, the marginal effectiveness of them is declining (Pfrommer et al. 2013, p. 24). When separating the no-service events into the ones, when customers are faced with empty or full stations, the number of events, when users were not able to rent a bike, was substantially higher. This may be overcome by adding bikes to the system (Pfrommer et al. 2013, p. 26).

Furthermore, the incentive reallocation scheme was found to be effective in decreasing service shortfalls, especially if only a small number of trucks are employed (Pfrommer et al. 2013, p. 26). Furthermore, the results let suggest that “price incentives are viable for repositioning bicycles in a PBS when the commuting rush hour is less prominent. For the London PBS, price incentives alone where shown to be enough to keep the service level above 87% on weekends without the use of staff. On weekdays, however, when many customers use the PBS to commute to work, price incentives alone are not sufficient to lift the service level substantially” (Pfrommer et al. 2013, p. 26).

3.2.2. Comparison of low, medium and high demand cases

The simulation created by Chemla et al. (2013) is another example for price incentives to manipulate the end station decision in public bicycle sharing systems. The effect of the implemented incentive is tested and compared for three demand cases (low, medium, high) and four system sizes (20, 50, 100, 250 vertices).

In this model the time needed by a user to travel from station *a* to *b* is a random variable (Chemla et al. 2013, p. 2). Customers of the system are assumed to arrive independently and are randomly assigned a destination. It is assumed that if a potential user is not able to rent a bike at the first station, she/he walks to another one (now aware of the situation in the system, once in it) to rent a bike. If no bike is found there neither, the process is repeated. However, each user has a maximum number of stations she/he is willing to explore as well as a limit to the searching time. If no bike could be rented within these limits, the user leaves the system unsatisfied. Regarding the pricing, prices are kept constant over time windows, but are different for distinct stations. Therefore, if two customers arrive at the same station in the same time window, they are charged the same. In contrast, a user arriving at another dock is charged a different price. Meaning, prices are attached to stations. In the underlying model the demand is seen as inelastic, hence, a certain level of demand is predetermined. (Chemla et al. 2013, p. 3)

The time, which users need to go from station *a* to station *b*, is deterministic (Chemla et al. 2013, p. 10).

In the simulator, users are described by (Chemla et al. 2013, p. 10):

- The maximum number of stations she/he is willing to explore in addition to the initial dock in order to find a bike before leaving the system.
- The maximum number of docks she/he is willing to explore in addition to the destination one in order to find a place to leave the bike before leaving the system. (At this point it has to be noted, that if the user does not find a free docking station, the bike disappears from the system.)
- The maximum time she/he is willing to spend in order to find a bike before leaving the system.
- The maximum time she/he is willing to spend in order to find a place to leave the bike before leaving the system.
- The price of one second spent by him/her with the bike. By default, the value is one, which means that the reference is the time spent with a bike.
- The price of one second spent by walking. For example, if this value is set at five, the disutility of one second walking equals five seconds riding a bike.

The simulation is tested in a low demand case (users are arriving in average every 5 minutes), medium demand case (each 2.5 minutes) and high demand case (each 1.5 minutes). Moreover, these levels of demand are employed in four different system sizes: having 20, 50, 100 or 250 vertices. Only one profile of users is analysed: the maximum number of station the user is willing to explore for renting and returning. The maximum time the user is willing to spend to find a bike is 600 seconds, while 900 seconds can be used to find a docking station for returning. Furthermore, the price of one second spent with the bike is one, while one second walking is valued by 2.1. Prices are updated every 15 minutes. (Chemla et al. 2013, p. 11)

The simulation is run for all these scenarios as well as for different methods of reallocation. Hence, no regulation at all, a one-step heuristic method as well as a one-step heuristic method with forecast are considered. Moreover, a two-step heuristic with forecast and a two-step one-stop heuristic with forecast are employed in the situation. Naturally, the pricing method got also taken into consideration (Chemla et al. 2013, p. 11). In the following, the performance of the different reallocation methods in the named system sizes are evaluated through the number of satisfied users, number of users who could not find a bike or no docking station and number of rejections. The focus will be laid on the prizing method. It has to be kept in mind that the prizing method was not employed in the largest system size situation of 250 vertices.

Results show that in the case of the low case demand, the pricing method was the technique with the smallest number of users who could not find a pike or parking spot throughout all sizes in which it was employed (20, 50 and 100). Furthermore, it was the method with the most satisfied users at a system size of 100. However, the pricing method has the second smallest number of satisfied users in the systems with 20 and 50 vertices. The largest system size of 250 shows rather similar outcomes for all methods regarding satisfied users and number of users, who could not rent a bike or find a free dock. (Chemla et al. 2013, p. 12)

When it comes to medium level demand, the pricing method has once again the smallest number of no bike and no parking spot occurrences for all three system sizes. Furthermore, this method yielded the highest number of satisfied users for the systems with 50 and 100 vertices. In the case of 50 vertices the one-step heuristic method with forecast generated the same number of satisfied users, hence, shared the first place. Although the pricing method yielded satisfying results through the bigger system sizes, in the case of 20 vertices the pricing technique resulted in the second smallest number of satisfied users. (Chemla et al. 2013, p. 12)

In case of high demand, the pricing method reported the highest number of satisfied users for the sizes 50 and 100, but once again the second smallest for the size of 20. Likewise to the medium and low demand scenarios, the pricing technique yielded the lowest numbers of users, who found no bike to rent or no free docking station to return, throughout all sizes. (Chemla et al. 2013, p. 12)

In conclusion, the pricing method becomes very efficient when the size of vertices becomes larger (Chemla et al. 2013, p. 14). This could be seen for small, medium and high demand scenarios. The pricing method resulted always in the highest number of satisfied user for the systems with 100 vertices and, in case of medium and high demand, also for the system size of 50 (Chemla et al. 2013, pp. 12). Hence, the pricing technique has shown to be a sufficient method for PBS' balancing through altering end-station decisions.

3.3. Price incentives employed in trip decision

In the studies of Chemla et al. (2013) and Pfrommer et al. (2013) price incentives were employed to manipulate the users' end-station selection. In the following, a different approach of price incentive employment will be discussed. Waserhole et al. (2012a, 2012b, 2013) and Waserhole and Jost (2012) analyse the following scenario: The user indicates at the beginning at station *a* where she/he wants to drive. Based on this, the customer is offered a price, which can be agreed on or rejected. If the user accepts the offering, a dock at the destination station is reserved, if the offer is rejected, the customer leaves the system (Waserhole et al. 2012a, p. 3).

It is assumed that the stochastic demand of customers, who want to travel from station *a* to *b* at time *t* for the charged price *p,* is known. Based on this assumption Waserhole et al. (2012a, 2012b) and Waserhole and Jost (2012) conducted substantial research on vehicle sharing system pricing regulation. They created a fluid approximation, optimized static pricing policies and FCFS flow pricing. These are further explained in the following subchapter.

3.3.1. The fluid approximation

For the fluid approximation, the assumption that demand is elastic is made, hence, price is used to influence the customer's behaviour (Waserhole et al. 2012a, p. 3). Therefore, a *Vehicle Sharing Systems Markovian Model* is created, with elastic demand, which is constant in time steps (Waserhole et al. 2012a, p. 4). The goal was to optimize the number of trips sold by the system. Furthermore, a simulation was run to compare the CLASSIC (fixed price set as the lowest possible) and FLUID (fluid heuristic) pricing policy in a homogeneous city. Their relative gain in terms of trips sold is evaluated (Waserhole et al. 2012a, p. 13). Additionally, the influence of possible gravitations and tides in homogeneous cities is evaluated through simulation (Waserhole et al. 2012a, p. 16).

In order to optimize the number of trips sold, only a continuous surjective demand function is implicated in which price can create any demand between zero and the maximum one (Waserhole et al. 2012a, p. 13). This means, in the closed queuing network with finite buffer and service time variation, a demand is given for every trip. “Each demand […] is represented by a server […] which has a time dependent service rate equal to the average number of clients willing to take a trip from station a to station b” (Waserhole et al. 2012a, p. 4).

For optimization of the given model the price is changed and, hence, the elastic demand. Therefore, price and demand are included as variable factors in the model. This is called the Stochastic *Vehicle Sharing System Pricing Problem* (Waserhole et al. 2012a, p. 6). “The Stochastic Vehicle Sharing System Pricing Problem amounts in setting a price for every trip in order to maximize the gain of the Vehicle Sharing System Markovian Model. Prices can be Discrete, i.e. selected in a set of possibilities, or Continuous i.e. chosen in a range. Pricing policies can be Dynamic, i.e. dependent on system’s state (vehicle repartition and period of the day), or Static i.e. independent on system’s state, set in advance and function of the trip and the time of the day” (Waserhole et al. 2012a, p. 6).

The modelled system has no direct interaction with the user, decisions are static and have to be taken in the beginning (Waserhole et al. 2012a, pp. 6). Moreover, the built mathematical programming model is based on continuous prices. As mentioned above, the existence of a continuous surjective function, which strictly decreases, is indicated and this function computes the demand for a given price (Waserhole et al. 2012a, p. 9). A SCLP program with the named objective to maximize the gain for the system can be seen in equation 4. a,b present the trips serving a trip demand D for all time steps t in the time period T (Waserhole et al. 2012a, p. 11):

$$(4) \qquad max \sum_{(a,b)\epsilon D} \int_0^T gain_{a,b}\,(t)\; dt.$$

Since the model is based on the deterministic approximation, it does not take the stochastic form of the demand into consideration (Waserhole et al. 2012a, p. 11). Furthermore, first only a fully homogeneous city, which means that the demand for each trip is equally likely, is considered (Waserhole et al. 2012a, pp. 12).

In the simulation stations have either a capacity of 10 docks with a total number of vehicles of 60% of total station docks times fleet of vehicles, or infinite capacity but the same number of vehicles. A day has 12 hours and only one way trips are considered. (Waserhole et al. 2012a, p. 13)

As mentioned above, the number of trips sold by the system was tried to optimize. Through the simulation the average number of trips sold by the CLASSIC way as well as by the FLUID policy is evaluated and the relative gain is calculated (Waserhole et al. 2012a, p. 13).

The performance of optimization was found to be highly related to demand intensity. “The higher the demand intensity is, the higher the improvement of the fluid heuristic […]” (Waserhole et al. 2012a, p. 14). However, this increase in the number of trips sold is reached on expense of the use of vehicles. This means that the use of bikes decreases due to favouring short distance trips in the system. (Waserhole et al. 2012a, pp. 14)

Furthermore, the influence of gravitation (i.e. hill) in a system was studied. For this purpose a homogeneous city was split into two equal parts and the demand for trips from part E to part F was increased, while the demand for trips from part E to part F was decreased (Waserhole et al. 2012a, p. 15). “Although FLUID is not improving a full homogeneous city, as soon as some gravitation appears the gain of using this heuristic increases significantly […]” (Waserhole et al. 2012a, p. 16).

Additionally, possible tides (i.e. morning or evening flows) in homogeneous cities were analysed. Therefore, the day got divided into three periods (6 am to 9 am, 9 am to 3 pm, 3 pm to 6 pm). Moreover, the city was split into two parts with different demand patterns. In the morning the demand for trips from E to F is high, while it is the opposite in the evening. “In cities with a uniform station capacity […], the optimization has more impact than cities with infinite station capacity […]. It might be explained by the fact that the system with infinite station capacity can absorb the tides. This shows the interest of a good station capacity sizing” (Waserhole et al. 2012a, p. 16).

It has been found that “the fluid approximation would be efficient in systems with high traffic and appropriate sizing. However for relatively low traffic systems, the fluid approximation policy seams worse than the classic policy” (Waserhole et al. 2012a, p. 18).

3.3.2. Optimizing symmetric and conservative static pricing policies

Furthermore, the fluid approximation has the problem that the number of states grows exponentially with the number of vehicles and stations. As it is based on a deterministic approximation the results are not optimal. Therefore, in the paper of Waserhole and Jost (2012) a stochastic, polynomial model, with constant demand and infinite station capacities as well as zero transportation times, is considered. Prices are the leverage, which means that there is also an elastic surjective demand dependent on price (Waserhole and Jost 2012, p. 4).

The goal of the paper is to elaborate a static policy through which the average throughput of the system can be maximized and which can be employed in real large PBS (Waserhole and Jost 2012, p. 8). In the following (equations 5 - 21) the linear programs for the optimal (in terms of trips sold) conservative and symmetric static policies for *N* vehicles in a system with *S* stations as well as directed demand (D) and D_u undirected trips are given (Waserhole and Jost 2012, pp. 12).

Symmetric and conservative policies are subclasses of the static one (Waserhole and Jost 2012, p. 4). For remembering: "Pricing policies can be […] Static i.e. independent on system's state, set in advance and function of the trip and the time of the day" (Waserhole et al. 2012a, p. 6). By employing static symmetric policies, the prices are set to encourage the same number of users to take a trip in each direction (Waserhole and Jost 2012, p. 9). Equations 5 – 12 give the optimal linear programs of symmetric policies for maximizing the number of trips sold (Waserhole and Jost 2012, p. 12):

$$max\, 2 \times \sum_{(a,b)\in D_u} \pi_{a,b} \times D_{max\ a,b} \tag{5}$$

$$s.t. \pi_{a,b} \le \pi_a \qquad \forall (a,b) \in D_u \tag{6}$$

$$\pi_{a,b} \le \pi_b \qquad \forall (a,b) \in D_u \tag{7}$$

$$(N-1) \times z + \sum_{a\in S} \pi_a = N \tag{8}$$

$$\pi_a \le z \qquad \forall a \epsilon D_u \tag{9}$$

$$\pi_{a,b} \ge 0 \qquad \forall (a,b) \in D_u \tag{10}$$

$$\pi_a \ge 0 \qquad \forall a \epsilon S \tag{11}$$

$$z \ge 0 \tag{12}$$

As mentioned above *S* represents the set of stations in the system with *N* vehicles and *D* are directed as well as D_u undirected trips. *a* and *b* are the stations, through which the trips for each pair of stations are included by *(a,b)*. The maximum demand is implemented through the variable D_{max}. "[…] only stations with associated variable (π_a, $a \epsilon S$) with values greater than 0" (Waserhole and Jost 2012, p. 12) are considered. *z* defines the ordered set of these values (Waserhole and Jost 2012, p. 12).

In contrast, static conservative policies aim to create the same level of demand for bikes as well as for docking stations in each station (Waserhole and Jost 2012, p. 13). Equations 13 – 21 give the optimal linear programs of conservative policies for maximizing the number of trips sold. The variables meaning can be taken from the previous paragraph (Waserhole and Jost 2012, p. 14):

(13)	$max \sum_{(a,b)\in S} \pi_{a,b} \times D_{max\ a,b}$	
(14)	$s.t. \sum_{(a,b)\in D} \pi_{a,b} \times D_{max\ a,b} = \sum_{(b,a)\in D} \pi_{b,a} \times D_{max\ b,a}$	
(15)	$(N-1) \times z + \sum_{a\in S} \pi_a = N$	
(16)	$\pi_a \leq z$	$\forall a \epsilon S$
(17)	$\pi_{a,b} \leq \pi_a$	$\forall (a,b) \in D$
(18)	$\pi_{a,b} \geq \pi_b$	$\forall (a,b) \in D$
(19)	$\pi_{a,b} \geq 0$	$\forall (a,b) \in D$
(20)	$\pi_a \geq 0$	$\forall a \epsilon S$
(21)	$z \geq 0$	

3.3.3. FCFS flow pricing

Likewise, Waserhole et al. (2012b) considered a deterministic approach to optimize different pricing methods. For this purpose, it is assumed that all trip requests are available at the beginning (Waserhole et al. 2012b, p. 3). The underlying system is based on the *First Come First Serve* (FCFS) flow principle. This means that a trip request is only accepted if a vehicle is available at the wished station at this point of time and a parking dock is free at the destination station at the wanted point of time. If the trip request is possible it generates a gain, the vehicle is removed from station *a* and a parking dock is reserved at station *b*. After the traveling time the vehicle is again available at station *b* (Waserhole et al. 2012b, p. 4).

In the *Priced FCFS Flow* the gain of the system at a given price level is evaluated (Waserhole et al. 2012b, p. 5). Each trip has a given price, which represents the maximum that the customer is willing to pay (Waserhole et al. 2012b, p. 4). The *Priced First Come First Flow* model is optimized by including price leverage with static pricing. This results in two pricing methods of FCFS Flow: *MAX FCFS FLOW TRIP PRICING* and *MAX FCFS FLOW TRIP PRICING* (Waserhole et al. 2012b, p. 5).

By employing the *MAX FCFS FLOW TRIP PRICING* method the induced Priced FCFS Flow is tried to be maximized by setting the optimized price for each trip (Waserhole et al. 2012b, p. 7). In contrast *MAX FCFS FLOW STATION PRICING* depends on the individual stations and colours them for the users. Hence, the price is an addition to take a vehicle in station *a* and to return it in *b*. Therefore, the user may understand more easily the different alternatives which trips are existent (Waserhole et al. 2012b, pp. 7).

Chapter 3 has completed the relevant literature review to answer research question 1. While operator-based reallocation techniques had been explained in the previous chapter, this one focused on agent-based balancing methods. As the upcoming empirical research is based on incentives in balancing methods, user-based reallocation techniques were described in more detail than operator-based ones.

Three kinds of incentives were found in existent literature: power of two choices, pricing to influence the end-station decision and pricing to impact the trip decision. As more incentives might be applicable for agent-based reallocation techniques, the following chapter deals with incentives on a general basis.

4. Incentives

Although many operator-based reallocation strategies exist and they are tried to be optimized, there are substantial costs related to this kind of rebalancing. Furthermore, employees shifting bikes from one station to another is time consuming and environmental polluting (DeMaio and MetroBike 2009, p. 50). Naturally, balanced demand would be the perfect solution, through which optimal performance of the system would be created. As this is not possible per se, incentives may be implemented to manipulate the demand in the system.

Incentives might be used to decrease or increase the demand for each station. In this manner return rates to push stations can be increased. Likewise, demand for renting from pull stations can be strengthened. For this purpose, the best working incentive(s), which would be accepted by users, has/have to be evaluated (like written down in research question 3).

The current chapter deals with incentives related to the reallocation problem in biking systems. First, distinct kinds of incentives and their general use are explained. Afterwards, monetary and non-monetary as well as their subcategories and their (potential) employment in bicycling systems will be analysed. Monetary rewards are used as a synonymous for financial rewards and are "of or pertaining to money" (Dictionary 2014). In the following, non-monetary incentives are defined as "compensation given in a transaction which does not involve cash. A non-monetary reward can consists of almost any material object such as jewellery, precious metals or an automobile for example. In business, a non-monetary reward can also be a service such as improvements made on a property or repairs done on a car" (Business dictionary 2014).

This chapter deals with the use of incentives in general as well as in reallocation of BSSs. Furthermore, different non-monetary and monetary incentives are listed and finally compared. In the course of this chapter hypothesis for the empirical research will be drawn.

4.1. The use of incentives

Incentives are used in many areas to evoke favourable behaviour. Companies use incentives to improve their managers' and workers' performance, governments to create public welfare as well as effective use of public goods and researchers to increase the response rate of questionnaires.

The use of incentives is controversial in literature. Some researchers claim that incentives are not necessary, as sufficient intrinsic motivation for well performance is given. Another argument against incentives is that the required task is too hard that even incentives are not sufficient for its' carrying out or that the incentive has a flat payoff frontier (Camerer and Hogarth 1999, p. 8). However, many studies proof the positive effect of incentives on preferred behaviour (Burgess et al. 2003, p. 16; Edwards et al. 2002, p. 4; Camerer and Hogarth 1999, p. 19).

There are numerous studies on the effect of incentives. Some of them as well as some characteristics of incentives are given beneath. Hence, how incentives work and the further used categorization will be pointed out in this section. Furthermore, first hypothesis will be stated.

4.1.1. How incentives work

Incentives have an effect on people's performance as they function like motivators. In general intrinsic, image and extrinsic motivation triggers distinct behaviours. Intrinsic motivation derives from the person her/himself. Image motivation is created by the social environment of a person. If a behaviour is favourable and visible to other, the person is more likely to act in an approving way. Extrinsic motivators are any conventional incentives like financial payment or goodies (Ariely et al. 2009, p. 544). Although intrinsic and image motivation can play a role in bicycle reallocation, this paper is based on extrinsic motivation. People, who have intrinsic motivation to have a well-functioning system and try to rebalance the system through their usage, may exist, but are certainly not enough to have the system balanced. Furthermore, image motivation may not be helpful, as this kind of motivator strongly relies on the social group. As most city bike users do not know each other, the social desirability effect is lost. Therefore, extrinsic motivation will be the focus for further work.

People react to incentives due to cognitive exertion, motivational focus and emotional triggers. Cognitive exertion is perceived if the receiver deliberates the task thoroughly due to the incentive. If the person's objectives are changed by the incentive, another motivational focus is created. In the case of emotional triggers "the incentive is a prerequisite for the agent to predict or emit their response" (Read 2005, p. 266). In the case of bicycle schemes the motivational focus is the most important. Although a problem awareness due to the incentive implication might arise, users will not develop sufficient intrinsic motivation, as explained above. In contrast, granted incentives are most likely perceived as additional value and may change the motivational focus.

Additionally, a distinction between relative and absolute incentive schemes can be made. Especially firms have to decide between absolute and relative incentives. Relative incentive schemes are based on the individual performance in contrast to a reference group. Absolute incentive schemes only depend on the individual actions and no comparison to other persons is needed (Bandiera et al. 2004, p. 2). A study on workers has shown that the productivity increased by 50%, when the scheme was changed from relative to absolute (Bandiera et al. 2004, p. 3). Likewise to the image motivation, relative incentive schemes depend on reference groups, which is too wide in public biking systems to have an effect. Hence, absolute incentives will be used in the empirical study.

As it can be seen, there are numerous kinds of incentives and their employment. Not all of these can be employed in the underlying context. In the following subchapter absolute incentives as extrinsic motivators are employed on the basis of a motivational focus change.

4.1.2. Categorization of incentives

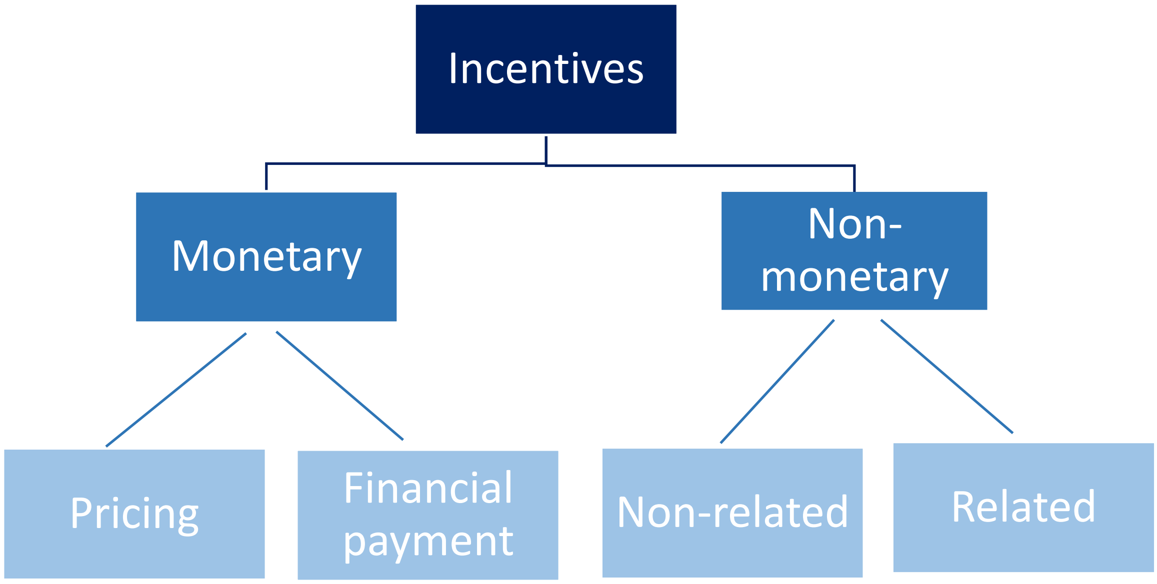


Figure 3: Types of incentives (Source: Own creation)

The incentives included in the further research are either monetary or non-monetary. Monetary incentives are mostly financial like sales commission. Non-monetary can be goodies given to the receiver like promotion without a pay raise (Campbell 1997, p. 3). Figure 3 shows their subcategories. In the context of bike-sharing systems monetary incentives can be financial payments and favourable or penalising pricing techniques. Non-monetary incentives can be related or non-related. Non-related non-monetary incentives are goodies or gifts handed out to the receiver, while related ones can be bonus time. The further explanation of these kinds of incentives and their relevance to the underlying topic will be discussed in the following subchapters.

In general, many studies have proofed the positive effect of non-monetary as well as monetary incentives on preferred behaviour (Burgess et al. 2003, p. 16; Edwards et al. 2002, p. 4; Camerer and Hogarth 1999, p. 19). Hence, the first hypothesis reads as follows:

Hypothesis 1: Incentives offered (monetary as well as non-monetary) will have a positive effect on users' willingness to go to the suggested end station.

4.2. Non-monetary incentives

In this section non-monetary incentives are discussed. As mentioned above, these can be related as well as unrelated to public bicycle schemes. Afterwards, a comparison of the two kinds of non-monetary incentives will be made and the second hypothesis will be drawn.

The main advantage of tangible non-monetary incentives are their actual cost and their perceived value. Due to relationships, high quantity or tax breaks a company may receive certain goods cheaper than individuals. In extreme the firm would have to pay nothing and the perceived value to the receiver is enormous. An example would be hotels. They can easily give away rooms in off-seasons and bear hardly any costs, but for the traveller the accommodation is of great value (Jeffrey 2002, p. 4). Therefore the main advantage of non-monetary incentives lies in the difference of perceived value for the receiver and actual cost for the provider.

Furthermore, non-monetary incentives are easily separated from regular monetary compensations like salary. Especially in terms of worker motivation, monetary incentives granted by the employer might be mentally added to the wage and, hence, can be confused with compensation. Although the receiver is aware of the incentive and naturally happy of its granting, the special and remarkable character of the incentive might be lost. Moreover, employees usually use their salary as reference point, which might diminishes the reward mentally. This is because the incentive probably seems small in contrast to the whole salary. (Kahneman and Tversky 1979, p. 277)

Additionally, preferable associations and separation to regular monetary compensation are mentioned as arguments for non-monetary incentives. Firms may provide goods or services which are evaluated as highly pleasurable, which makes the incentives more remarkable and less forgettable. Therefore, the value of the incentive is not only evaluated on its monetary value, but also emotionally (Loewenstein et al. 2001, p. 269). Hence, additional value to non-monetary incentives can be created through emotional associations.

4.2.1. Non-related non-monetary incentives

Non-related non-monetary incentives are goods or gifts handed-out to the receiver. This can be anything from regional park passes or free ride on a trade fair to the participation in a lottery. Main non-monetary incentives used in literature are lottery tickets and donations (Stadtmüller 2005, p. 7). Additionally, Metropark passes (Ryu et al. 2005, p. 96) are used in research. A survey on 1,004 American adults has yielded the results that the most favourable incentive for employees is a trip to a destination of their choice, followed by a shopping spree at stores of their choice, home improvement as well as beautification items and season tickets to the favourite entertainment venue. Electronics were the least favoured non-monetary incentives in this survey. Therefore, it can be seen that incentives, which offer a choice, are preferred (Hutson 2002, p. 76).

As mentioned, donations are one of the main used non-monetary incentives in the literature. Hence, a donation incentive will also be included in the following empirical research. However, some people do not trust donation institutions or do not see the need to donate. Hence, it is assumed that the user's donation behaviour affects the level of impact of donation incentives. This is presumed in hypothesis 2:

Hypothesis 2: Donation as an incentive will have a stronger effect on users' willingness to go to the suggested end station, if the user has donated at least once in the last year.

Other non-monetary incentives, which are non-related to the topic approached in this thesis, are online coupon bonuses and point systems for online platforms. An online coupon bonus was, for example, proposed in the King County's business plan for bike sharing. "A reward program that offers gift certificates of credits towards future membership fees to encourage riders to ride uphill" (Alta Planning + Design 2012, p. 66).

Another option would be a points system for honoring on online platforms, which may work in the following way. Every time a user goes to the suggested end station she/he earns a (some) point(s) (the amount may be connected to the additional effort). These points, when gathered enough, can be redeemed at certain partner online platforms and, hence, are used as a coupon which involves choice.

Online coupon bonuses function the same way as traditional bonuses, but are redeemed in internet. As these non-monetary incentives are heavily connected to the customers' use of internet, hypothesis three states the following.

Hypothesis 3: Online coupon bonuses as well as the point system for online platforms will have a stronger effect on users' willingness to go to the suggested end-station, if the user purchases online at least once a month or more often.

So far no non-related non-monetary incentives were used in studies about reallocation problems or real bicycle-sharing systems. Therefore, no evaluation of its usage in this setting can be given.

4.2.2 Related tangible non-monetary incentives

Related tangible non-monetary incentives can have many forms like giving autonomy, recognition and praise (Ezigbo and Court 2011, p. 128). In the context of public bicycle schemes bonus time for riding is used as a related tangible non-monetary incentive. As most bicycle-sharing systems are operated on the basis of an initial free time period, which is mostly 30 minutes to an hour, and fees are only paid afterwards, extra time can be an attractive incentive for users. Especially, if bonus time can be stored and used when needed.

In practice there is only one PBS which is operated with an incentive approach for the reallocation problem: The public bicycle program of Paris called Vélib'. The operators have introduced the so called *V+* concept. As some stations are uphill and it takes more time and effort to go there by bike, these stations are usually empty. Naturally, most users rent a bike uphill to drive downwards, but do not drive back by bike. The operators started the *V+* concept to encourage users to drive uphill. Customers who hand in their public bikes in one of the 100 designated uphill stations are granted 15 minutes extra time (DeMaio and MetroBike 2009, p. 50). These extra minutes can be saved and used for any future trip (Vélib 2014).

When the *V+* concept was introduced in summer 2008, the credit was granted 314,443 times within the first three months. One of the co-inventors of Vélib' stated that the distribution of bicycles costs about $3 per bike. He remarked that giving customers a time credit for future use or handing out monetary incentives would increase distribution efficiency at a way lower cost than operator based. (DeMaio and MetroBike 2009, p. 50)

Furthermore, a private BSS also employs incentives. As mentioned in the introduction, the company Social Bicycles charges, a convenience fee if bikes are left outside of the stations. This convenience fee is provided as an incentive to other users, who might pick the bike up from its location. (Christensen 2014)

For the given topic, bonus time is suggested to be more effective as an incentive than goodies. Hence, it is hypothesized that users rather react to related incentives than to non-related ones, which results in hypothesis 4.

Hypothesis 4: Related non-monetary incentives will have a stronger effect on users' willingness to go to the suggested end-station than non-related non-monetary incentives.

Despite all these arguments for non-monetary incentives, some studies conclude that non-monetary incentives are less effective than monetary ones (Church 1993; Ryu et al. 2005, p. 91). This will be further elaborated in subchapter 4.4. Comparison of non-monetary and monetary incentives. First, monetary incentives will be discussed.

4.3. Monetary Incentives

In this section monetary incentives are analysed. They are often called financial incentives in literature. As already mentioned, monetary incentives are further divided into financial payment and pricing techniques. In the course of this sub-chapter, the last hypotheses are given.

4.3.1 Financial payments

Financial payments are often used in literature, especially to increase response rates. Edwards et al. (2002) did a systematic review of postal questionnaires to identify effective strategies to grow response rates (Edwards et al. 2002, p. 1). They found that if money was used as an incentive, the responses were more than doubled. This result was found even if the incentives were not conditional to response (Edwards et al. 2002, p. 3). Furthermore, their model predicted a decreasing marginal benefit. Hence, increasing the incentive from $1, connected to a doubled return rate, to $15, boosted the rate by a factor of 2.5 (Edwards et al. 2002, p. 4). Other studies also provided support for this decreasing marginal benefit. A study showed that an incentive of $5 did not have a greater effect than an incentive of $1 (Mizes et al. 1984, p. 797). Another one found an increase of 1% when moving from $5 to 10$ incentives (Warriner et al. 1996, p. 557). Therefore, the effect of monetary incentives results from the reward itself and hardly from its value.

Other studies on incentives in questionnaires have yielded similar results. Church (1993) found an increase of 19% of response rates when monetary incentives were used. However, this rise was only created if the incentive was offered with the first send-out of the questionnaire. Jobber et al. (2004) also provided support for the positive effect of monetary incentives. Their results showed that the value of an incentive did not matter, but an incentive itself increased the response rate by 15% to 17% (Jobber et al. 2004, p. 24).

In the context of reallocation in bicycle sharing-systems, financial payment as incentive was used in a study by Pfrommer et al. (2013). The rewards are offered to customers of the system when they arrive at a full station and want to give back their bikes. Hence, the users have to approach a neighbouring station, which results in additional effort. For some of these neighbouring stations an incentive is offered. The users value the incentive against the additional effort and choose the station with the maximum value. This consists of the "maximum amount of money offered minus the distance times the marginal cost" (Pfrommer et al. 2013, p. 7).

The study provided support for the employment of financial payments as incentives in public bicycle schemes. "Customer payments were shown to be a means of reducing service shortfalls, particularly when few repositioning trucks were in operation" (Pfrommer et al. 2013, p. 26).

4.3.2 Pricing techniques

The demand for stations with a critical amount of bikes can also be balanced through pricing. The pricing can be dynamic, dependent on the system's state, or static, set in advance and fixed for a certain period of time (Waserhole et al. 2012a, p. 6). Pricing techniques can also be seen as monetary incentives, as customers are persuaded to choose trips which bear the lowest costs for them.

One way of implementing pricing techniques into a public bicycle system is to let potential customers choose an end-station. Then they are given a price for the trip. This price may be accepted or refused. If the consumers decide to accept the price, a parking spot at the end station is reserved (Waserhole et al. 2013, p. 150). For this mode the presumptions that demand is elastic and a price for each level of demand exists are made. Hence, a minimum price would create demand. In extreme the system pays the user (Waserhole et al. 2013, p. 153; Weikl and Bogenberger 2013, p. 356). Through this approach users may be more aware of the different alternatives of possible trips (Waserhole et al. 2012b, pp. 7).

In contrast, the study of Chemla et al. (2013) is based on inelasticity for a basic level of demand. The prices are attached to stations instead of to trips. Hence, the users arriving at different docks are charged different prices (Chemla et al. 2013, p. 3). Especially for a larger number of bikes in the system, the pricing method was found to yield good rebalancing results (Chemla et al. 2013, p. 14).

Pfrommer et al. (2013) have shown that price incentives were sufficient to keep the service level above 87% in London's BSS on weekends. No operator-based reallocation was employed. However, if high demand is present, like on weekdays, price incentives alone were not enough to keep the service at an efficient level. (Pfrommer et al. 2013, p. 26)

As already mentioned in the introduction, most BSSs offer their service for free for a given time period. Hence, users only have to pay if they pass this time period. As PBS are mostly introduced for parking space requirements, roadway costs and environmental reasons (McClintock 2002), making profit is often only second-rate to the operators. Therefore, due to the cheap costs connected to the use of BSS, it is assumed that pricing techniques will have a limited impact on users' choices. As a result hypothesis 5 is drawn as follows.

Hypothesis 5: Financial payments will have a stronger effect on users' willingness to go to the suggested end-station than pricing techniques.

4.4. Comparison of non-monetary and monetary incentives

Although monetary and non-monetary incentives are said to be useful, several studies proof the greater effect of monetary incentives than of non-monetary ones (Church 1993; Ryu et al. 2005, p. 91). For example, the increase in response rates of monetary incentives was found to be 13.2% in contrast to 7.9% of non-monetary ones (Church 1993, p. 8). One reason for this may be that money has a universally understood value, but the value of non-monetary items is not that visible. For example, if a pass to a regional park is used as an incentive, the value depends on the receiver's attitudes towards a visit in the park. If the person has wanted to go there anyway and now got the entrance for free, the value is higher than if the receiver is not interested to visit the regional park at all (Ryu et al. 2005, p. 91).

Furthermore, as mentioned above, people prefer incentives which offer choice (Hutson 2002, p. 76). Although non-monetary incentives may leave some decisions of where and how to honour the reward, financial payments grant the biggest freedom possible. The same is true for pricing, as the saved money from choosing the cheaper alternative can be spent on anything. Hence, people tend to value gifts lower than cash (Ryu et al. 2005, p. 93).

Due to these studies and their results the last hypothesis, which will be tested, states:

Hypothesis 6: Monetary incentives will have a stronger effect on users' willingness to go to the suggested end-station than non-monetary incentives.

This chapter dealt with the general use and effect of incentives. Furthermore, the categorization into non-monetary and monetary incentives, which will be used in the upcoming empirical research, was explained. These categories were discussed more deeply as well as their potential use in BSSs. In line of this, the six hypotheses, which will be tested in chapter 6, were drawn. Therefore, the current chapter helps to answer the research questions 2 and 3 and gives basic information and the necessary hypotheses for the empirical research.

5. Empirical research

The empirical research is based on the BSS of Vienna called *Citybike*. Citybike has been operated by the advertising agency GEWISTA since 2003. The system consists of 120 statins and more than 1,500 bikes. Users have to register online with a debit card or a Citybike card and pay an amount of one euro for registration, which will be credited on the user's account. Citybikes can also be rented with credit cards, which is especially comfortable for tourists. Stations can be localized via the terminals or online. At these plans the current situation of each station - if it is full, empty or in balance - is shown. The users receive the first hour for free at each rental. After one hour an amount of one, two or four euros have to be paid for each started hour. (Wien GV 2015; Citybike 2015)

5.1. Questionnaire

In order to answer the elaborated hypotheses and compare the effectiveness of the different incentives, a questionnaire was asked to be filled out by Citybike users. It was distributed online and in print and took about five minutes to be filled out. The different channels are further described in the subchapter 5.2.

All questions are based on related literature, which will be pointed out in the following. Furthermore, the population in question consists exclusively of Citybike users. This is based on the assumption that only users of the BSS are able to give valuable information for its improvement. Furthermore, a part of the questionnaire is based on the usage of Citybike, which can only be answered if the participant is a user. Hence, the sample should only include users registered in the system, which will be guaranteed by the screening question. Furthermore, German users are focused as most respondents are believed to live in or next to Vienna. Therefore, the questionnaire is elaborated in German.

The questionnaire consists of four parts. The first one deals with the user's behaviour in the system and includes the screening question to assure that all respondents are Citybike users. Afterwards the general willingness as well as the willingness, when incentives are offered to go to the suggested end-station, are asked to be evaluated. Thirdly, questions about general behaviours like doing sport or donating are listed. Finally, demographic data is gathered.

Most questions are compulsory, as they are believed to be not sensitive and respondents are able to understand and answer them. Only one which is thought to be sensitive is stated as optional, which will be pointed out in the following. All questions except the ones dealing with reasons and barriers to Citybike usage are single choice. The reason for this is that the questions are elaborated to have all possible options or state an *other* alternative. Hence, the participants are suggested to be able to choose one option. Furthermore, having clear answers will result in less diluted results and a better outcome of the study.

5.1.1. Questions about the behaviour in the system

As mentioned above, the first part of the survey deals with the users' behaviour in the BSS. First, a screening question is given, which should exclude non-users of Citybike from the survey. The participants are asked to state how often they use Citybikes and have five alternatives from *daily* to *never* (Zikmund and Babin 2010, p. 404). If *never* is marked, the respondent will be deleted from the sample, as all respondents have to be a user of Citybikes, to get valid results.

Additional to the screening question, questions about the participant's usage of Citybike are asked. This part includes whether people use Citybikes instead of buying bicycles or additionally. Therefore, participants are asked whether they own a bicycle and if they are a tourist in Vienna. Furthermore, the respondents are asked how long they use Citybikes on average. It is known that the most common ride lasts 10 minutes and that the average ride length is 22.5 minutes (Dechant 2013, p. 16). Nevertheless, this question is essential as one of the potential incentives is bonus time, which might only be appealing to a respondent if his/her average usage period exceeds one hour, as the first hour is free of charge. A study by Citybike concludes that 95% of all rides are for free (Dechant 2013, p. 16). The possible answer options vary from *less than half an hour* to *more than 4 hours*.

Moreover, the main reasons and barriers to Citybike usage, help to understand the behaviour of the participants. The reasons for the usage of public bicycle schemes are based on a study by Fishman et al. (2012), in which comfort, environmental consciousness and the low expenses as well as the fitness factor were stated. Moreover, Citybikes as a complement to public transportation and its proximity to the working place are listed as optional reasons. Respondents are allowed to choose several answer options, as more reasons might be the cause for their usage. This question is important for comparing the different reasons for usage with the most effective incentives. Hence, users, who mainly use the BSS due to environmental reasons, may be attracted by different incentives than users who use Citybikes owing to its comfort.

The barriers for potential usage were extracted from the King County bike Share Business Plan (Alta Planning + Design 2012, pp. 53) as well as a bike system feasibility study (TransLink 2008, pp. 29). Eight reasons were identified to be potential obstacles for a Citybike usage. These are compulsory wearing of a helmet for children under 12 years, the weather, lack of infrastructure for cyclists or of nearby docking stations as well as missing Citybikes, when arriving at a docking station, or full end-stations, when attempting to return one. Further barriers might be the costs as well as longer traveling distances and the rather low speed of bicycles in contrast to trains or cars. Participants may also choose several answers for this question due to the same reasons like for the last one. Likewise, the importance of the question is based on its comparison with the preferred incentives. Additionally, respondents are given the chance to state other reasons and barriers to Citybike usage in the last two questions by being offered an *other* answer choice.

5.1.2. Incentive block

The part measuring the effect of distinct incentives is the core part of the questionnaire and is mainly based on the studies of Clawson and Rouse (1992), Lu and Yan (2007) and Burgess (2005). These studies were chosen due to their similar topics. All of them deal with incentives and motivating factors.

Clawson and Rouse (1992) conducted a study about potential motives and incentives of older people to be volunteers. In terms of their research they conducted a survey about incentives, which are most frequently identified by volunteers. Clawson and Rouse (1992) created a 15-item scale in which each incentive was described through five statements. Furthermore, a five-point scale was used to measure the intensity of preference related to the incentives (Clawson and Rouse 1992).

Likewise, Burgess (2005) grouped three to seven items in each category and tested their consistency. The respondents rated the items on a one to six scale (Burgess 2005, p. 332). Similarly, Lu and Yan (2007) had a five-point Likert scale indicating from *strongly disagree* to *strongly agree*. The participants rated the perceived incentives of partnering in China. They had also the option of a *no idea* answer (Lu and Yan 2007, p. 244).

Therefore, the core part of the questionnaire of this study was created in a similar way. First, an item evaluating the general willingness of Citybike users to follow the terminal’s instructions was introduced. This is seen as an important part at the beginning of the incentive block to be able to measure the effect of the offered incentives. Hence, a better understanding can be given by comparing the users' general willingness with their willingness, when introducing an incentive.

Afterwards three statements for each incentive category were created. The four categories are derived from the theory chapter: financial payment and pricing techniques for the monetary incentives and non-related as well as related non-monetary rewards. The answering option for financial payment dealt merely with the reception of cash. Pricing techniques included free as well as cheaper rides. Related non-monetary incentives were given through granting bonus time. Online coupon, a point system for online platforms and donations presented non-related non-monetary incentives.

Similar to Lu and Yan (2007), the resulting twenty statements can be rated on a five Likert scale from *strongly disagree* to *strongly agree*. However, a *no idea* option is not given, as the participants are believed to be able to answer the question. Therefore, respondents are not provided with an easy out, as they are suggested to have attitudes towards the distinct rewards (Zikmund and Babin 2010, p. 359). Nevertheless, point three can be seen as a neutral point in the rating scale, in case a respondent is not able to evaluate an incentive or not willing to give an answer.

5.1.3. Questions to the participant's behaviour

This subchapter is focused on the participant's sport, donation and online shopping habits. These questions are important to compare the incentives' effects. The question how often the respondent does sport shows whether athletic participants are more willing to follow the terminal's instructions. The respondent has five options to choose from daily to less than once in the month. Furthermore, the participant is asked about his/her donation habit. For this the last year is taken as reference and the respondents have to choose between five alternatives from having donated weekly to not at all in the last 12 months (Neumayr and Schober 2008, p. 112). This question is important for hypothesis 2.

Likewise, the online behaviour is essential to answering hypothesis 3. Precisely, this hypothesis deals with the online purchase behaviour and the related incentives. However, to get a whole picture of the respondents' online behaviour also the online frequency is asked. Therefore, participants are asked how often they are online and how often they purchase online. They can choose from seven options from several times a day to less frequent than once a year (Zikmund and Babin 2010, p. 404).

5.1.4. Demographic questions

At the end of the questionnaire some demographic questions are asked to be filled out. These help to understand whether some incentives are more effective in distinct sections of population. First, the sex of the respondents as well as their age are questioned. When it comes to age, the participants are asked to write down the number and no answer options are given. Therefore, a rational variable, which can be used for regressions to find linear relationships, is gathered.

Furthermore, respondents are asked whether they live in a city, urban area or on the countryside. Moreover, they can choose between nine options to describe their occupation plus an *other* alternative, if they feel to be not covered by the given ones. The stated answer options are pupil, apprentice, military or social service, student, employee, employer, housemen/ -wife, unemployed and retired.

The last question deals with the respondent’s monthly net income. The four answer options are groups from less than euros (EUR) 500 to more than EUR 3.000. As this might be a sensitive question, it is the only optional one. However, as it is assumed that numerous respondents would not answer it when it is highlighted as optional, it has been included in a subtle way. Hence, in the print version of the questionnaire a little star is placed at the end of the question and at the end of the page the star says that the question is not compulsory. In the online version a hint field can be clicked on, which states that this question is optional.

The final questionnaire can be found in appendix 1 of this thesis.

5.2. Sampling

As mentioned above, the sample is based on the population of Citybike users. This was ensured by the screening question in the questionnaire. Respondents who stated to *never* use the services of Citybike were excluded.

The population, which is subject to analysis, consists of all registered Citybike users. These were 480.000 people in 2013. However, this number increased in the last year (Citybike 2014). Hence, the number of the population is thought to be approximately 500.000.

The main demographic characteristic of the population in question will be stated according to a study in 2010. It was based on data from 31 667 users, which were gathered between 2004 and 2007. From this study it can be drawn, that the underlying population is mainly formed by the younger half of the overall population. Precisely, 80% of the users are under 40 years old (Schneeweiß 2012, p. 56). Especially, the age group 20 to 29 is strongly represented. 52% of male and 59% of female Citybike users are part of this age group (Schneeweiß 2012, p. 58). Furthermore, 60% of Citybike users are male and 80% live in Vienna (Schneeweiß 2012, p. 56).

As the majority of Citybike users fall in the age group of 20 to 29, they are assumed to be reachable via online tools. Hence, they were employed to gather data from the sample. Additionally, the print version of the questionnaire was used to also reach people, who could not be reached through online channels.

The questionnaire was generated on Umfrageonline.com, which is a website for conducting online surveys. As mentioned above, all questions were compulsory, except the last one dealing with the income level. Furthermore, only the questions dealing with the motivators and obstacles were set to allow multiple answers. Unfortunately, the screening question could not be set to end the survey with participants who choose the *never* answer. Hence, even if respondents chose the *never* option they were led to the following questions. However, they were excluded from the sample manually before analysing the data. This is described in the next subchapter 5.3. dealing with data description.

First, snowball sampling was employed. Known Citybike users were asked to conduct the survey and to forward it to other Citybike users they know. This was done by E-mail or through social media. The link to the survey was shared on some personal Facebook pages.

Afterwards, simple random sampling was employed to reach a variety of Citybike users. Therefore, the link was posted in news on the websites *GamingXP.at* and *Wien-konkret.at* at the beginning of September 2014. These websites were chosen as their readers are mainly from Vienna.

As already mentioned above, social media was also employed for sampling. In fact, Facebook, LinkedIn and Twitter were used to reach Citybike users. Especially Facebook offered a wide variety of options to grasp the target group. Hence, the link was posted in the closed groups *Diplomand/Diplomandin an der Uni Wien*, *Club der Citybike Wien Benutzer*, *BWL/ IBWL Erstsemester 2013/14 Uni Wien*, *Gruppe Wien* and *BWZ Elite, der echte Ort um*

BWL zu studieren. Moreover, the following Facebook public groups also contained the link to the survey: *Sport in Wien*, *Uni Wien*, *WU-Flüchtlinge am BWZ*, *IBWL/ BWL am BWZ*, *WU Wien - Wirtschaftsuniversität Wien* and *Radfahren in Wien*. Especially the last group *Radfahren in Wien* has to be highlighted, as a lot of its participants conducted the survey at hand. Furthermore the link was also posted on several Facebook pages, which had a connection to Vienna. These pages were *vienna.info*, *Wiener Linien*, *Wiener Wiesn-Fest*, *I love Vienna*, *Vienna University of Technology* and *Fahrrad fahren in Wien*.

Through all these groups, pages and websites it was tried to reach as many Citybike users as possible. In order to give less frequent online users a chance to be part of the survey, the questionnaire was handed out at several Citybike stations in Vienna. People who rented or brought back a bike were personally asked to fill out the questionnaire. All this sampling was conducted from mid of August to end of September 2014.

5.3. Data description

Through all these channels 351 filled questionnaires could be gathered. 55 were taken from personal distribution and 296 conducted online. However, 61 online questionnaires were not finished. From the remaining 235 participants, 33 stated that they do not use Citybikes in the screening question. Hence, a valid number of 202 questionnaires online filled out and 55 printed ones, making in total 257 respondents, will be used in the following analysis.

First, a data description of the sample (257 respondents) will be given. Afterwards in the chapter *6. Results*, the hypotheses will be tested and their outcomes will be stated. Additionally, further tests with respondent behavior in the system, personal behavior and demographic data will be made and if believed to be of importance stated in the subchapter *Further analyses*.

Except for the final question about the monthly net income and the question about donation behavior, all questions were answered by all respondents. Hence, in the following for all descriptions and hypotheses a sample of 257 persons is used. One respondent did not answer the question about donating in the last year. 16 participants did not state their monthly net income, which leaves 256 and 241 valuable answers for these analyses.

5.3.1. Citybike usage

First, the description of the users' practice in the Citybike system will be given. This includes their usage frequency and duration as well as their bicycle ownership. Additionally, the question if the respondents are tourists in Vienna, is part of this subchapter. Furthermore, an image of motivators and obstacles to Citybike usage will be drawn.

More than half of the respondents use Citybikes less than several times a month. 40% of the respondents use Citybike several times a week or several times a month. In contrast only 6.2% use Citybikes daily. The exact percentages of Citybike usage can be seen in figure 4. It has to be mentioned that due to the exclusion of non-Citybike users the answer option *never* is not shown in graph 4.

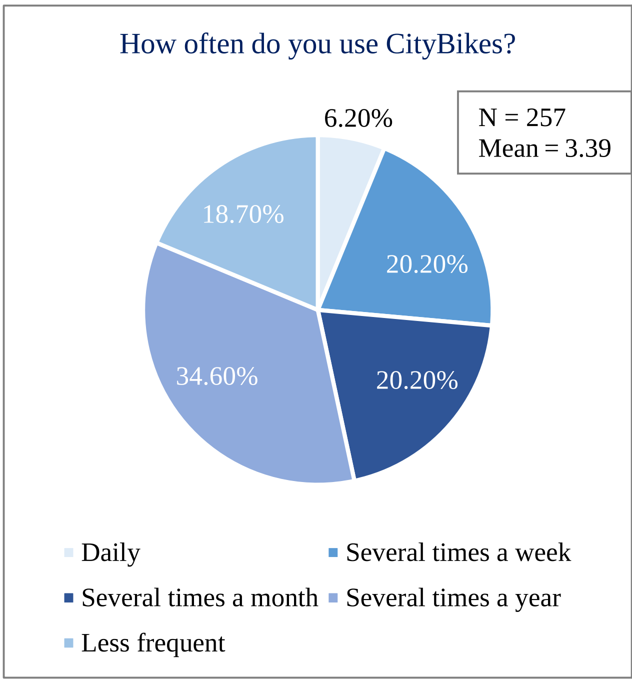


Figure 4: Citybike usage frequency
(Source: Own creation)

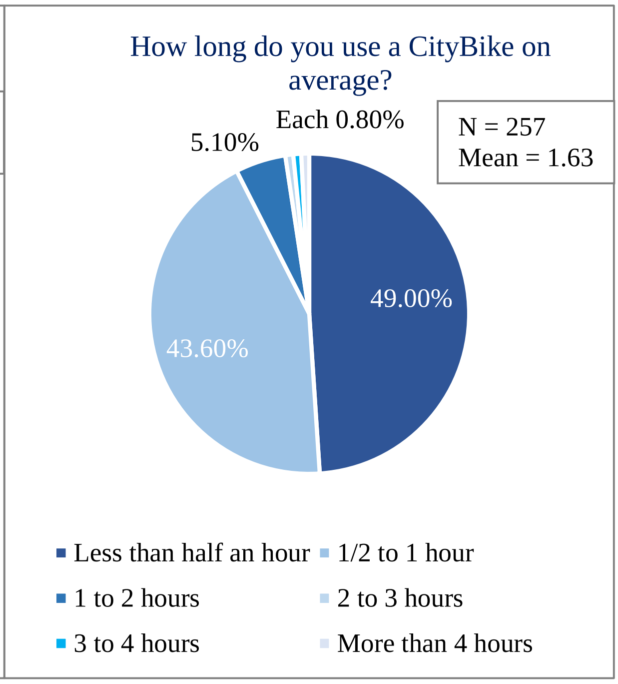


Figure 5: Citybike usage duration
(Source: Own creation)

Citybike is designed to primarily overcome short-term distances. This can also be seen in the data presented here. More than 90% use Citybikes on average up to one hour, hence, during the time which is for free. Only 2.4%, which makes it six out of 257 respondents, use Citybikes longer than two hours on average. The exact distribution can be taken from figure 5.

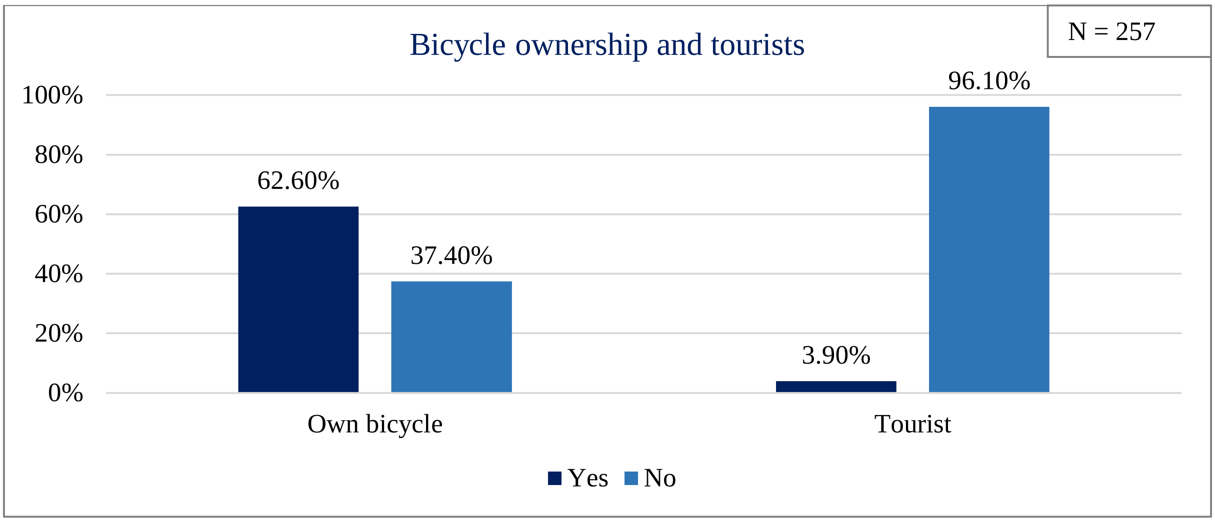


Figure 6: Bicycle ownership and tourists (Source: Own creation)

Furthermore, most respondents stated that they own a bicycle. This can be explained by some of the following motivators. Not surprisingly, more than 96% of the sample lives in Vienna. This is expected, as Citybike offers its services exclusively in Vienna. Hence, mainly residents of Vienna use it. The numbers of bicycle ownership and tourists are illustrated in graph 6.

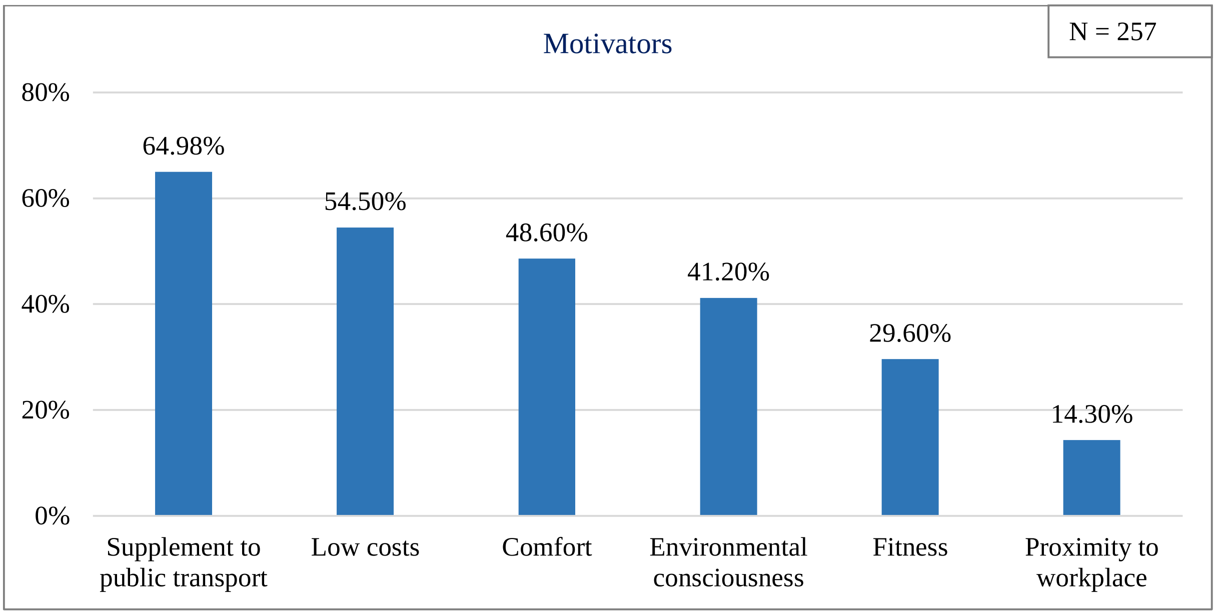


Figure 7: Motivators (Source: Own creation)

Two very interesting factors are the motivators and obstacles to Citybike usage. The motivators and their frequency of being named can be seen in figure 7. More than 60% of the respondents claimed Citybike's supplement to public transport to be a reason for its usage. The majority of participants also named the low costs to be a cause for being customers. Comfort was the third most often named motivator, followed by environmental consciousness. Less than a third of the respondents claimed fitness to be a motivator to use the BSS and the least popular motivator is the Citybike's proximity to workplace.

Additional to the motivators just explicated, respondents had the chance to state other reasons for their Citybike usage. 17 respondents (6.61%) named supplement to their own bike as a motivator. This factor includes a temporarily damaged or not available bike due to being somewhere else or even stolen. One respondent also stated that Citybike is a good supplement to the own bike, if it should not be left somewhere at night. Furthermore, fun of riding (City)bikes was highlighted seven times (2.72%). Especially, nice weather, time for yourself and riding a bike with friends were mentioned in this context. The motivators *one-way trip* and *fast reaching a destination* were each named four times (1.56%). Moreover, sightseeing and the easy rental as well as that it is always available, were reasons to use Citybikes for two respondents (0.78%).

Interestingly, almost the half of the respondents stated no nearby stations to be an obstacle to Citybike's usage. Therefore, nearby stations may not be a motivator, but a lack of them is definitely an obstacle. Nevertheless, the most important obstacle are empty or full stations. Hence, the problem with rebalancing the system was found to be a major one as almost 80% of the respondents referred to it. This can be seen as a further argument for dealing with the reallocation problem of BSSs.

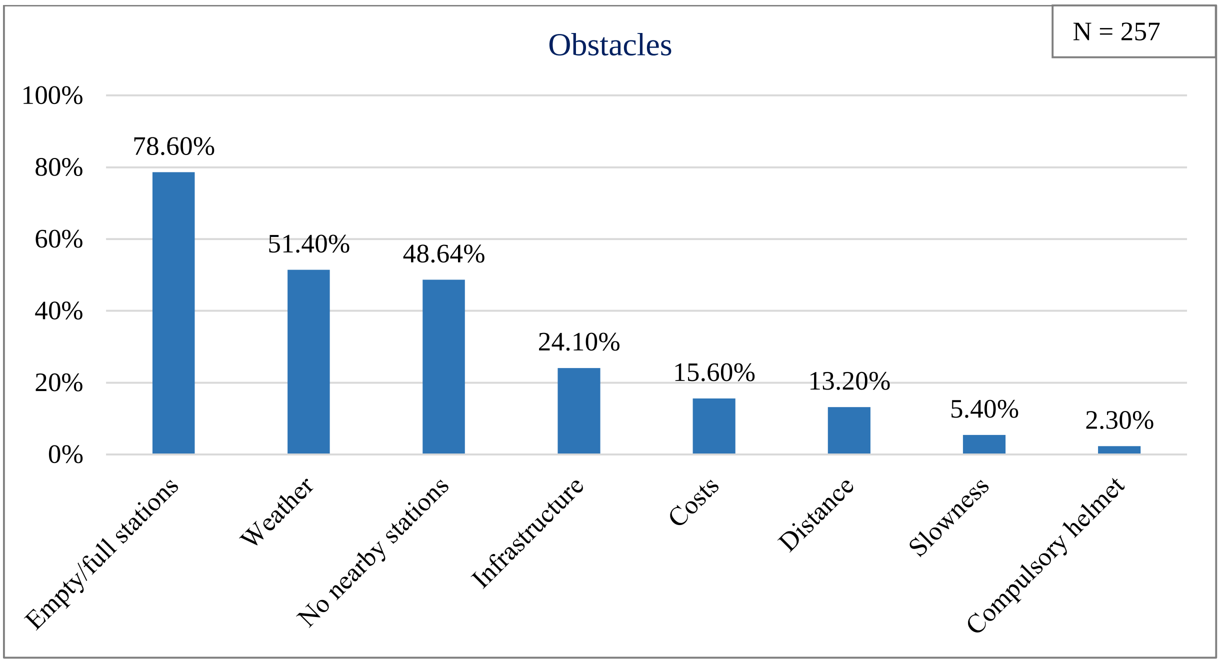


Figure 8: Obstacles (Source: Own creation)

Still half of the respondents picked the weather as an obstacle, while only a quarter claimed the lack of infrastructure to be a problem in Citybike usage. Another interesting fact is that while more of the half of the respondents claimed the low costs of Citybike to be a motivator, 15% stated the involved costs to be an obstacle. Hence, the included costs are perceived very differently by the respondents. The obstacle trip distance was named by more than 10%, while the slowness of the mode of transport and compulsory helmet wearing are found to be minor problems for Citybike users, as it can be seen in figure 8.

Additionally, old bikes like lacking gears or poor quality were mentioned to be an obstacle by eight persons (3.11%), hence, it is seen as a greater problem to Citybike usage than compulsory helmet wearing for kids. Likewise, old terminals and outdated technology at the stations was also mentioned by two participants in this section. Six people (2.34%) stated a lack of comfort as a restriction to their usage. This includes the need of locking Citybikes in one of the stations, not being able to rent a bike without debit card at hand and the need to remember the password. Also horning cars in the streets were mentioned in the context of lacking comfort. Furthermore, danger and exertion were named from a person as an obstacle. Being in possession of an own bicycle reduces BSS usage according to two respondents.

5.3.2. Incentive block

In the previous chapter 5.1., the construction of the incentive block was described. It consists of the two main groups monetary and non-monetary incentives. These are further split into financial payment and pricing technique groups for monetary incentives and related and non-related ones for the non-monetary incentives. Furthermore, the general willingness is included in the incentive block to compare the effectiveness of the incentives with it.

As it can be seen in figure 9 the point system for online platform was evaluated at lowest and, together with the online coupon incentive, lower than the general willingness to pursue the terminal’s suggestion. In contrast, the donation incentive and bonus time were evaluated at best, followed by financial payment and free trip incentives. The variances of all financial payment items are the biggest, which means that the respondents were most heterogeneous about this kind of incentive. Interestingly, the donation and the online platform incentives, which scored highest/lowest, have some of the lowest standard deviations. Meaning that the participants homogenously rated them on a high/low level. The variable general willingness has the smallest variance.

Incentive	Mean	Std. D.
General willingness	2.68	1.25
Financial payment 1	2.98	1.45
NR donations	3.2	1.33
NR online coupon	2.55	1.39
Financial payment 2	2.88	1.45
Related 1	2.88	1.42
PR1 cheaper	2.86	1.35
Related 2	3.01	1.41
PR 2 cheaper	2.85	1.35
Related 3	2.96	1.41
PR 3 free	2.92	1.38
NR online platform	2.39	1.30
Financial payment 3	2.77	1.49

Chart

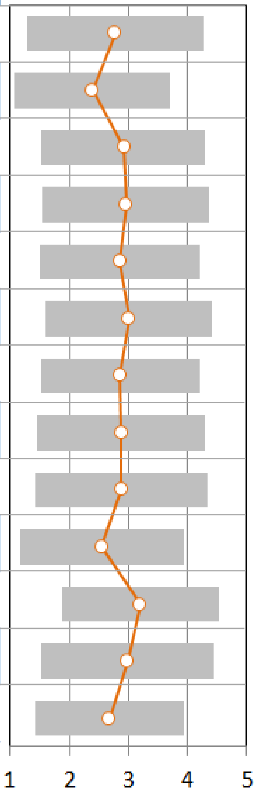


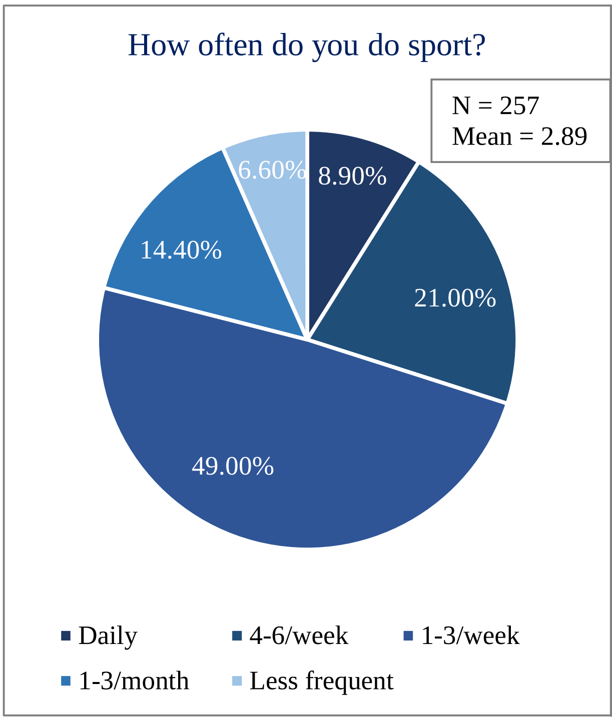
Figure 9: Incentives (Source: Own creation)

5.3.3. Personal questions

In the following a picture about relevant behavior related to the offered incentives is drawn. This involves the sport frequency, donation behavior and online behavior.

70% of the respondents exercise one to six times a week. Only a minority does sport on a daily basis, even less participants claim to exercise less frequent than once a month. All percentages of the answering options can be seen in figure 10.

Graph 11 shows the donation behavior of the respondents. It has to be mentioned that one person did not answer this question, hence, this data set is based on 256 responses. Almost 80% claim to have donated in the last year, while only 16% state that they did it on a monthly basis. Almost 37% donated occasionally and a quarter of the respondents even less frequent.



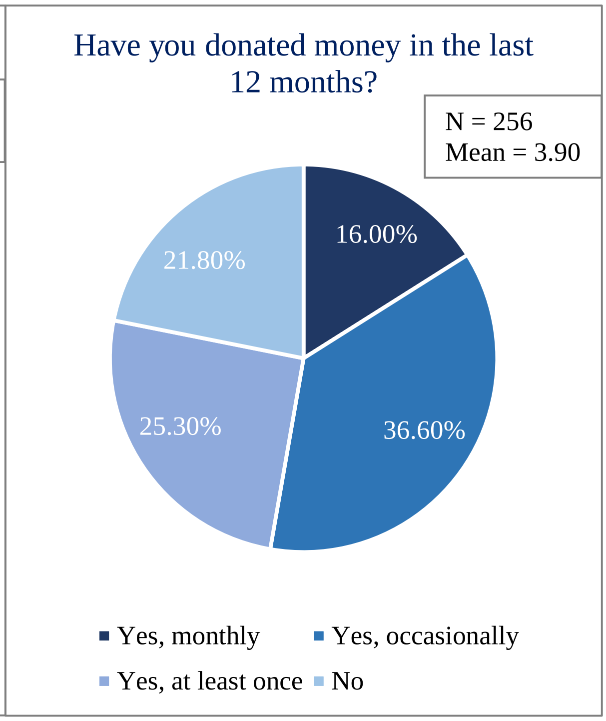
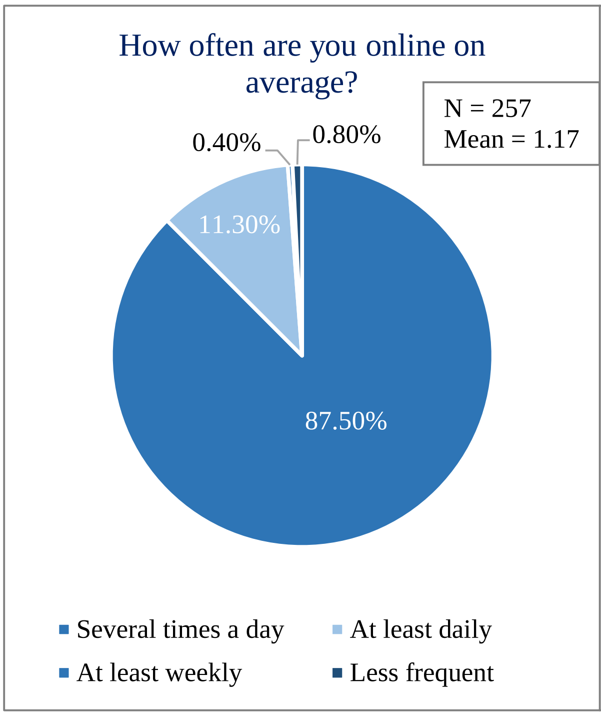


Figure 10: Sport frequency
(Source: Own creation)

Figure 11: Donation behavior
(Source: Own creation)

The online behavior factor is formed of two questions, one dealing with the online frequency the other one with the online purchase frequency. The online frequency is rather homogeneous with almost 99% to be online at least daily. In contrast, the online purchase frequency is more diverse. Almost 39% state that they purchase online at least monthly and more than 32% at least once per quarter. 10% purchase online more often than monthly, while the remaining 18% do it less frequent than quarterly. All exact figures of the factor online behavior can be seen in graphs 12 and 13.



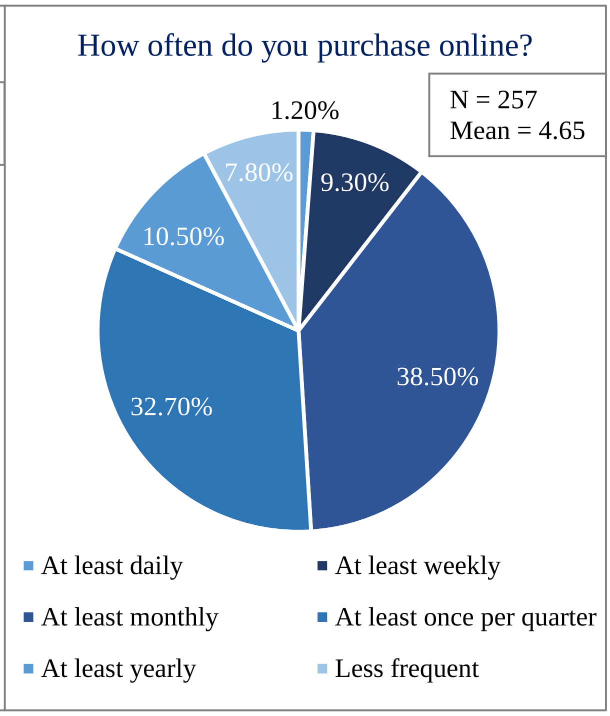


Figure 12: Online frequency
(Source: Own creation)

Figure 13: Online purchase frequency
(Source: Own creation)

5.3.4. Demographic questions

In order to find possible relationships between demographic variables and the effectiveness of distinct incentives the variables occupation, income, place of living as well as age and sex were asked in the questionnaire.

More than 60% of the respondents were male, which fits to the actual usage distribution of Citybikes (Schneeweiß 2012, p. 56), which was stated in the subchapter 5.2. Furthermore, most of the participants are between 19 and 35 years old. Almost a fifth of the respondents are over 35, while only 1% is under 19 years old. As 62.6% are between 20 and 29 years old and 87.9% are under 40, the population of Citybike users is also well presented in respect to age (Schneeweiß 2012, p. 58). The exact sex and age distribution of the underlying sample can be found in table 1.

		Age					Total
		<19	19-25	26-35	36-45	45<	
Sex	Male	1%	21%	27%	7%	6%	**61%**
	Female	0%	15%	17%	5%	2%	**39%**
Total		**1%**	**36%**	**44%**	**12%**	**7%**	**100%**

Table 1: Data description (Source: Own creation)

When it comes to occupation, two main groups were encountered which form, almost half and half, 85% of the respondents. These are employees and students. The missing 15% consist half of entrepreneurs and to smaller parts out of unemployed, housewife/-men, pensioners, pupils and community/ military servants. Graph 14 illustrates the occupations of the respondents.

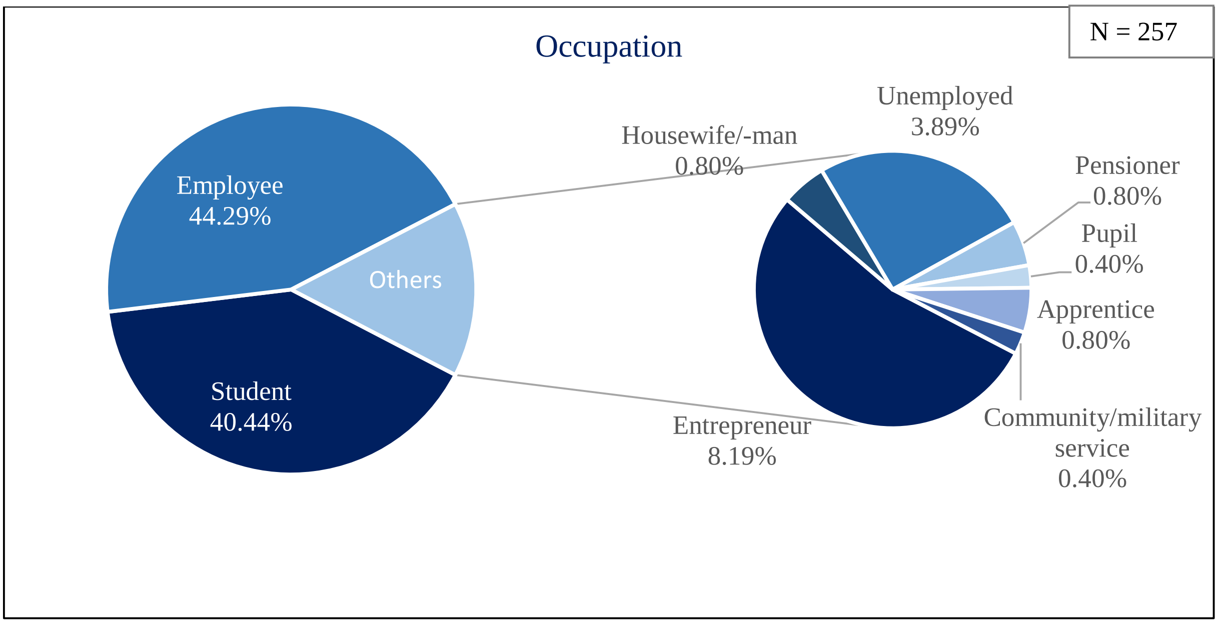


Figure 14: Occupation (Source: Own creation)

It is not surprising that almost 90% of respondents live in a City, as the service of Citybike is only provided in Vienna (figure 16). Likewise the income distribution (figure 15) was predictable as most of the respondents are at a rather young age and 40% are studying. Hence, more than 60% of participants have a net income of less than 1,500 euros per month. A quarter of the respondents earns EUR 1,500 to EUR 3,000 monthly. It has to be highlighted that 6.20% did not answer this question, hence, the data set consists of 241 answers.

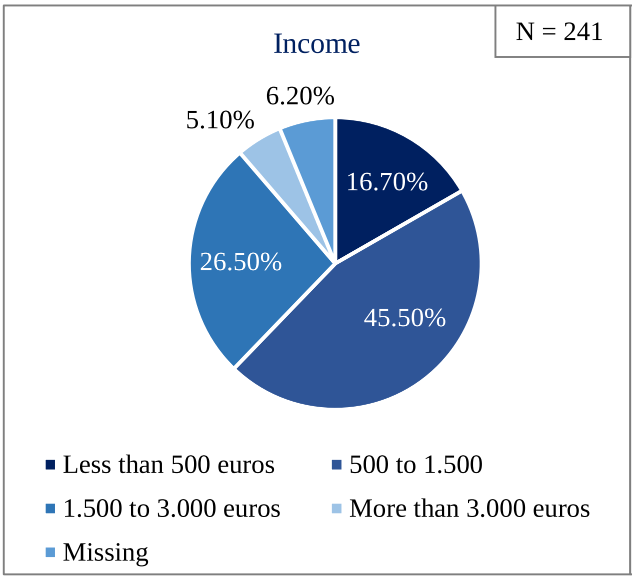


Figure 15: Income
(Source: Own creation)

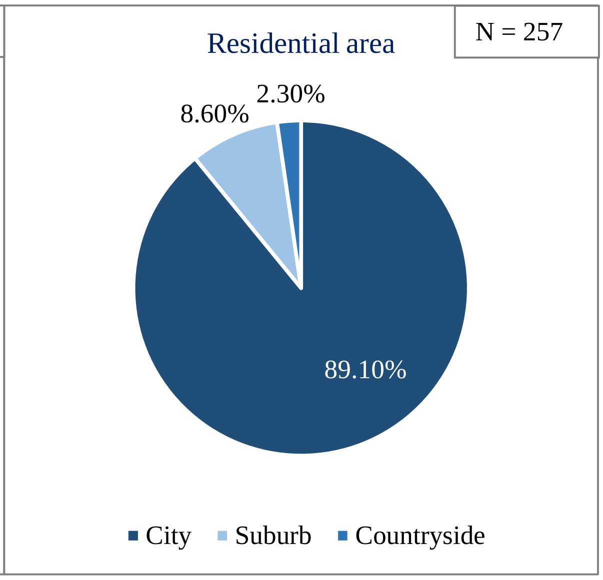


Figure 16: Residential area
(Source: Own creation)

Chapter 5 gave all necessary basic information for the empirical research. Hence, it built the foundation for the following chapter, which will answer research questions 2 and 3. In line of this chapter, the creation of the questionnaire, its four blocks and the individual questions were described. Furthermore, the sampling as well as the targeted population and the employed channels for questionnaire distribution were explained. In the last subchapter the gathered data were described block by block to give the reader an overview over the data set. With the data set described, which fits well to the real Citybike population, the stated hypotheses are tested in the next chapter.

6. Results

The hypotheses elaborated in the fourth chapter of this work will be tested based on the dataset described in the previous subchapter. This chapter is divided into the hypotheses, meaning that each subchapter deals with one hypothesis. Furthermore, at the end a chapter called *Further analyses* deals with further comparisons and potential relationships, which might be of interest in terms of the topic approached. Additionally, the announced tests for influence of system related behaviour, personal behaviour and demographic variables on the effect of the incentives will be done in the subchapter 6.7.

The hypotheses are stated in the same order as they were drawn in chapter 4. First, the general assumption about the impact of incentives on the respondents' willingness to go to the suggested end-station is analysed. Then distinct non-related non-monetary incentives and their effectiveness will be analysed taking into consideration related behaviour of the participants. Thirdly, the distinct sub-groups of non-monetary as well as monetary incentives will be compared. Eventually, a comparison of the evaluation of the two main groups of monetary and non-monetary incentives will be made.

For testing the hypotheses and analysing the data, the statistical program SPSS has been used. All relevant presumptions and their tests as well as their outcomes will be stated. Furthermore, each tested hypothesis will be interpreted whether it has been found to be supported or rejected.

6.1. Hypothesis 1

In this subchapter the first hypothesis will be answered. It states:

Incentives offered (monetary as well as non-monetary) will have a positive effect on users' willingness to go to the suggested end-station.

For this purpose, the incentive block in the questionnaire is analysed. Hence, the average points of all offered incentives can give a clue about the willingness of users to go to the suggested end station. In the questionnaire the user were asked to state on a five point Likert scale whether they agree or not agree to go to the suggested end-station with an offered incentive. Hence, a high average number of points would indicate a high willingness, while a low average would discover the opposite.

The mean of all variables in the incentive block, except the first one measuring the general willingness, is 2.86 with a variance of 0.967. Therefore, the average willingness to pursue the offered incentives is a little higher than the neutral point of the scale. Furthermore, the average points of the incentive block is compared with the mean on general willingness. In this question consumers were asked whether they would go to the suggested end-station positive effect of offered incentives.

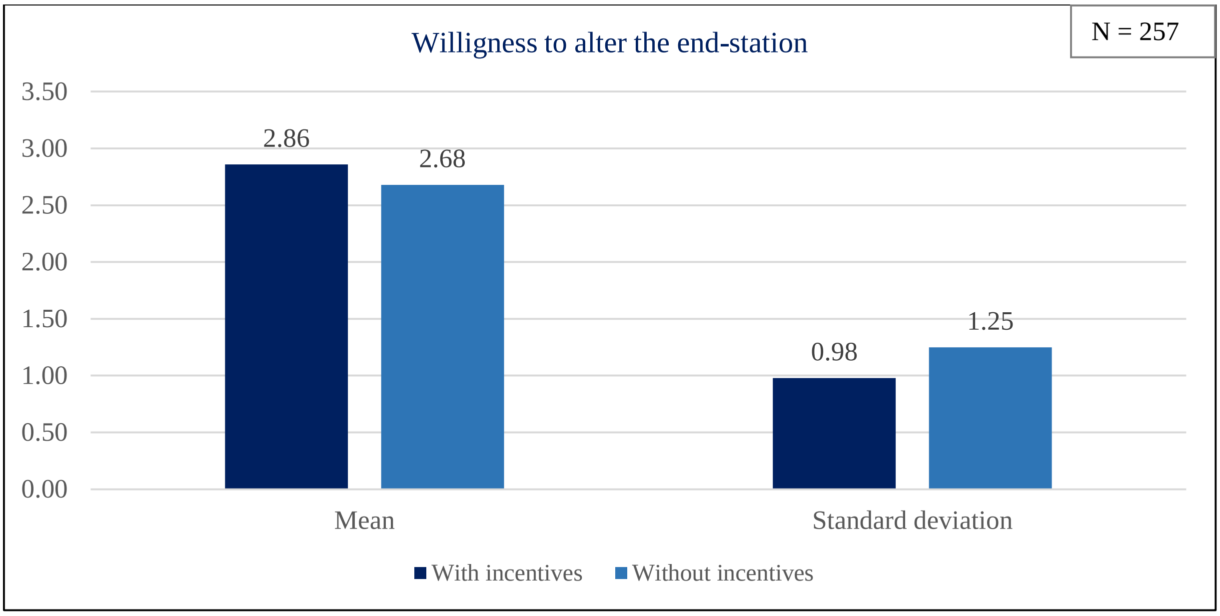


Figure 17: Comparison of willingness with incentives and general willingness (Source: Own creation)

The general willingness variable's mean lies at 2.68 and it has a standard deviation at 1.25. Hence, this mean value is shortly beneath the average of the user's willingness with offered incentives. Especially, the standard deviations show a difference. The general willingness has a greater variance than the variable combining all incentives. Mean and standard deviation of the general willingness variable and all incentives together can be seen in figure 17.

Furthermore, the Paired-sample t-Test can be employed to compare the variable *general willingness* and the one representing all offered incentives. However, when testing for its presumption of normal distribution, it is found that the variable *general willingness* is not normally distributed. The computed variable *With-incentives* would meet this assumption. However, the non-parametric Wilcoxon Matched-Pairs Test is used to gather valuable results. It is found that there is a significant difference (P-value < 0.05) between the evaluations of these variables.

Hence, hypothesis 1 is supported although the positive effect of the offered incentives on users' willingness to go to the suggested-end station is found to be rather small.

6.2. Hypothesis 2

The second hypothesis deals with the relationship of the donation incentive and the donation habits of the person. The donation incentive is one of the non-monetary non-related incentives and is measured with a five-point Likert scale. The donation habit was evaluated as part of the respondents' behavior. In exact terms hypothesis 2 states:

Donation as an incentive will have a stronger effect on users' willingness to go to the suggested end-station, if the user has donated at least once in the last year.

As hypothesis 2 states *at least once in the last year* the mean of people who have donated in the last 12 months, will be compared with the ones who did not. Furthermore, these means are put in contrast to the overall mean. It has to be considered that one respondent did not answer the question about his donation habit. Hence, the following analyses will be based on a sample of 256.

In overall, the donation incentive reached a value of 3.2 out of five. If only respondents are counted, which have donated in the last year, the mean lies at 3.22. The respondents, who have not donated in the last 12 months, evaluated the donation incentive, with a value of 3.14, slightly lower. The stated outcomes are summarized in table 2.

	Overall	Have donated at least once	Not donated
% of respondents	99.61%	78.13%	21.88%
Mean on donation incentive	3.2	3.22	3.14

Table 2: Donation behavior and donation incentive (Source: Own creation)

Once again, SPSS is used to look for a potential relationship between these variables. As the donation behavior question has brought ordinal data, Spearman's Rho or Kendall's Tau can be used to find correlations. Furthermore, one-tailed p-values are calculated due to the directional nature of the hypothesis. However, all p-value are above the significance level of 0.05. Hence, any potential relationships are not significant and no correlation could be found.

Moreover, the independent t-Test can be used to compare the respondents, who have donated at least once in the last year, with the ones, who have not donated in the last year. The dependent variable, which is the donation incentive, is ratio and independent observations are encountered.

Homogeneity of variances and normal distribution are assumptions for the independent t-test. Homogeneity of variances is given by a non-significant Leven-test. However, the test shows that the underlying data set is distributed non-normally. Hence, the Independent-Samples Kruskal-Wallis Test has to be used. The p-value is with 0.585 over the confidence level, which means that no significant difference between respondents' evaluation of the donation incentive based on their donation behavior was found. Therefore, hypothesis 2 is not supported.

6.3. Hypothesis 3

Hypothesis 3 is similar to hypothesis 2 by comparing respondent behavior with the effectiveness of a related incentive. In this case the two related incentives, which are of interest, are the online coupon bonus and the point system for online platforms. The participant behavior variable in question is the online behavior. More precisely:

Online coupon bonuses as well as the point system for online platforms will have a stronger effect on users' willingness to go to the suggested end-station, if the user purchases online at least once a month or more often.

In table 3 the mean score on the point system as well as the coupon incentive are given for all respondents, participants (who purchase online at least monthly) and the ones (who bought online less frequent than monthly). There is an equal distribution in the data set between the latter two groups. Overall, the respondents scored 2.55 on the coupon and 2.39 on the point system incentive. People, who purchase online at least monthly, had slightly higher scores on both incentives, while people, who buy online less frequently, rated these incentives marginally lower.

	Overall	**Have purchased at least monthly**	**Less frequent than monthly**
% of respondents	100%	49.03%	50.97%
Mean on coupon incentive	2.55	2.59	2.51
Mean on point system	2.39	2.42	2.37
Mean on combination	2.47	2.50	2.44

Table 3: Online purchase behavior and online incentives (Source: Own creation)

Furthermore, a combination of the scores on the coupon incentive as well as point system were calculated based on their means. Before computing this new variable, an exploratory factor analysis (EFA) is conducted to see whether the two incentives can be grouped. The three assumptions sampling adequacy (Kaiser-Meyer-Olkin (KMO) Criterion = 0.5), sphericity (Bartlett's test is highly significant) and lack of multicollinearity (R matrix is above 0.00001) are met. Furthermore, direct oblimin rotation and Kaiser Criterion are used to determine the number of factors. One factor is found for which both loadings of the incentives are above 0.4. Hence, the combination variable can be created. For this combination the overall mean lies at 2.47. Furthermore, the same tendencies as before could be found. Respondents, who purchase online at least monthly, had higher scores on the combination than participants, who purchase less frequent. The exact figures can be seen in table 3.

As in hypothesis 2, the independent t-test can be used to find possible relationships. The assumption of homogeneity of variances is met for all three incentives (groups), while none of them is distributed normally. Therefore, the Mann-Whitney U-test is employed. However, all p-values lie above the cut-off point of 0.05. Hence, hypothesis 3 is also not supported.

In order to give a whole picture of the online behavior of the sample the variable online frequency will be considered as well. Apart from the online buying behavior, participants were asked to state their online frequency. 87.5% of the respondents claimed to be online several times a day. Based on these data of online behavior the sample is split into three groups: online intensive, mixed and online less intensive participants. Online intensive respondents are online several times a day and purchase online at least monthly. Online less intensive persons are online at least daily and purchase online less frequent than monthly. Respondents, who do not fit in any of these groups, are either online very frequently but do not purchase online or online rarely but purchase relatively often in internet. Hence, these participants form the group of mixed online.

	Overall	Online intensive	Mixed online	Online less intensive
% of respondents	100%	45.14%	46.3%	8.56%
Mean on combination	2.47	2.53	2.36	2.52

Table 4: Combinations of online behavior and online incentives (Source: Own creation)

The comparison of the mean scores of the combination of the online incentives shows that online intensive respondents values these incentives about the same as online less intensive ones. Mixed online respondents scored lowest on online coupons and point system.

Likewise to hypothesis 2 it is looked for a potential bivariate correlation. Therefore, the variables of online frequency and online purchase frequency as well as the online coupon incentive, point system and the combination of them is taken. As the hypothesis is directional, one-tailed p-values are selected. However, all p-values are above 0.05, which indicates that no correlation between these variables can be found. Therefore, hypothesis 3 is not supported.

6.4. Hypothesis 4

In this hypothesis the two groups of non-monetary incentives are compared. Related non-monetary incentives are represented by bonus time. Donation, online coupon and point system incentives form the non-related ones. The hypothesis at hand suggests that the former kind of incentives has a stronger impact on the wanted respondents' behavior than non-related ones:

Related non-monetary incentives will have a stronger effect on users' willingness to go to the suggested end-station than non-related non-monetary incentives.

First, EFA is conducted to see whether these two groups can be created on basis of their loadings. The three assumptions sampling adequacy (KMO Criterion = 0.75), sphericity (Bartlett's test is highly significant) and lack of multicollinearity (R matrix is above 0.00001) are met. Furthermore, direct oblimin rotation and Kaiser Criterion are used to determine the number of factors and included variables. Two factors can be distinguished, one is loaded highly by all related non-monetary incentives (above 0.95), the other one includes the online non-related incentives (both over 0.86). However, the donation incentive loads on both factors: 0.48 on the related group and 0.24 on the non-related one. Hence, it should be included to the first factor. Nevertheless, it will be included to the non-related group, as it also loads there sufficiently (> 0.4), for testing this hypothesis. If there are any interesting outcomes, when the donation incentive is put in the related group, will be analyzed in sub-chapter 6.7. *Further analyses*.

Incentive	Mean	Std. Deviation
Non related 1 (donations)	3.20	1.33
Non related 2 (online coupon)	2.55	1.39
Non related 3 (online platform)	2.39	1.30
Related 1	2.88	1.42
Related 2	3.01	1.41
Related 3	2.96	1.41
Non related group	2.71	1.02
Related group	2.95	1.36

Table 5: Non-monetary incentives (Source: Own creation)

Means and standard deviations of all non-monetary incentives are given in table 5. The donation incentive is rated substantially higher than online coupons or online platform incentives. In contrast, all related incentives are rated about the same, which is no surprise as they were all represented by bonus time. The difference in the non-related incentive group will also be further analyzed in 6.7. *Further analyses*.

To answer the hypothesis approached, two new variables are calculated. The means of all non-related incentives build the new variable *non-related*, while the same is done for *related*. In the previous table 5 the means and distribution of these new variables can be seen as well as they are shown in figure 18.

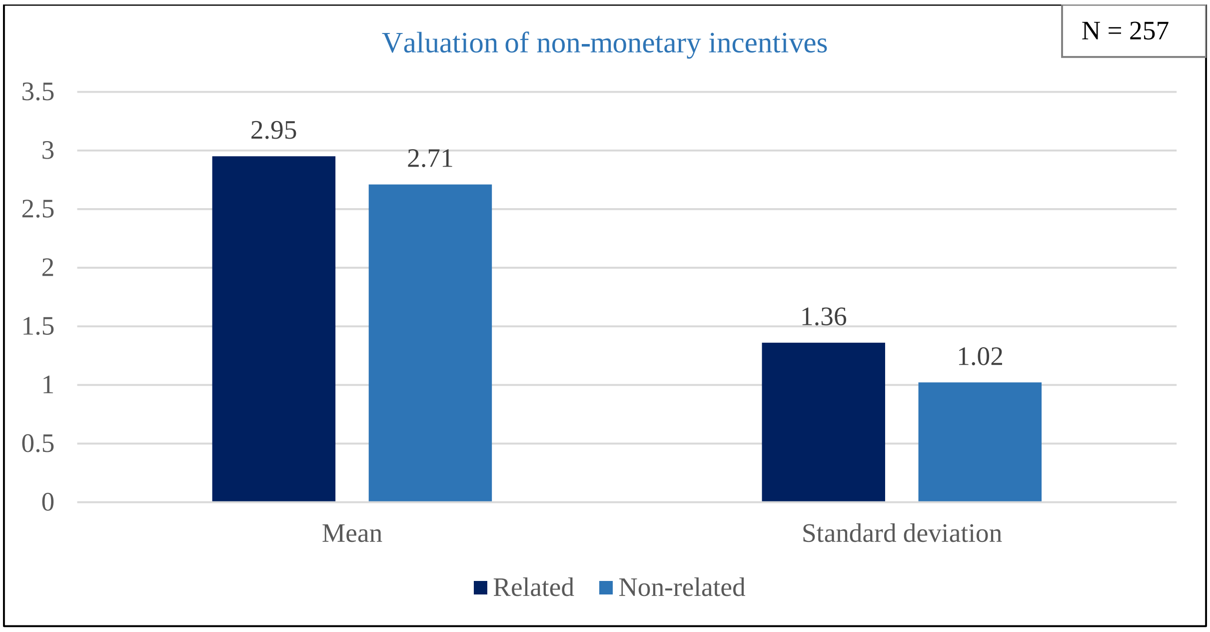


Figure 18: Valuation of related and non-related non-monetary incentives (Source: Own creation)

The *related* group has a mean of 2.95, while *non-related* scores an average of 2.71. Hence, related incentives did get evaluated better than non-related ones. Furthermore, related incentives were also scored higher than the average of all incentives, which was 2.86. In contrast, non-related incentives were evaluated lower than all incentives together. Both standard deviations are rather high, which shows that the participants were heterogeneous about these incentives' evaluation.

Furthermore, due to the within-group design of hypothesis 4 and the ratio nature of the values, the Paired-sample t-Test can be used to compare them. However, the assumption of normal distribution is found to be violated. Hence, the non-parametric test Wilcoxon Matched-Pairs test is used. The p-value lies at 0.007, hence, is lower than the significance level. This states that there is a significant difference in evaluation of related and non-related incentives. As a result related non-monetary incentives are evaluated significantly higher, hence are suggested to have a greater impact on the users' willingness than non-related non-monetary incentives. Therefore, hypothesis 4 is supported.

6.5. Hypothesis 5

Like hypothesis 4 dealt with non-monetary incentives, hypothesis 5 focuses on monetary ones. The effectiveness of financial payments is compared with the efficiency of pricing techniques. In the questionnaire pricing techniques were presented by gratis or cheaper trips. Financial payments were given in the form of monetary payout of two euros. These are packed in hypothesis 5:

Financial payments will have a stronger effect on users' willingness to go to the suggested end-station than pricing techniques.

First, the means of all these incentives are compared. As it can be seen in table 6 they are rather equally scored. Financial payment 1 and 2 were evaluated rather high in contrast to the pricing techniques, which promised cheaper trips. However, the pricing technique, which promised a free ride, was rated with 2.92 second highest of these incentives. Only the first financial payment has a higher mean with 2.98.

Incentive	Mean	Std. Deviation
Financial payment 1	2.98	1.45
Financial payment 2	2.88	1.45
Financial payment 3	2.77	1.49
Pricing technique 1 (cheaper)	2.86	1.35
Pricing technique 2 (cheaper)	2.85	1.35
Pricing technique 3 (for free)	2.92	1.38
Financial payment group	2.88	1.38
Pricing technique group	2.88	1.19

Table 6: Monetary incentives (Source: Own creation)

It has to be mentioned that the financial payment incentives lost on average 0.1 points at each mentioning, which might have several reasons. One cause may be the loss of attractiveness by taking into consideration and comparing it with other incentives. Financial payment 1 was mentioned as the first incentive and financial payment 3 as the last one. Another interesting fact is that pricing technique 3, the one offering a free ride, was substantially rated higher than the two pricing techniques offering only cheaper trips.

Likewise to previous group creations, EFA has to be used to verify clustering. Once again, it is tested for sampling adequacy, sphericity and lack of multicollinearity. With a KMO Criterion value of 0.78, a highly significant Bartlett's test and R matrix greater than 0.00001 all of these assumptions are met. Through employing direct oblimin rotation and Kaiser Criterion two factors are determined. One group includes all financial payment incentives (all loading above 0.9) and the other one consisting of all pricing techniques (loadings are greater than 0.82). Therefore, a financial payment and a pricing technique group are created. All means of the individual incentives as well as of the groups can be taken from table 6.

The financial payment incentive and pricing technique groups are further compared. By comparing these groups an interesting fact is discovered: they scored equally at a mean of 2.88. Only the standard deviation shows a difference. The respondents had a more similar attitude towards pricing techniques than towards financial payment. The exact figures of the mean and standard deviation values can be taken from figure 19.

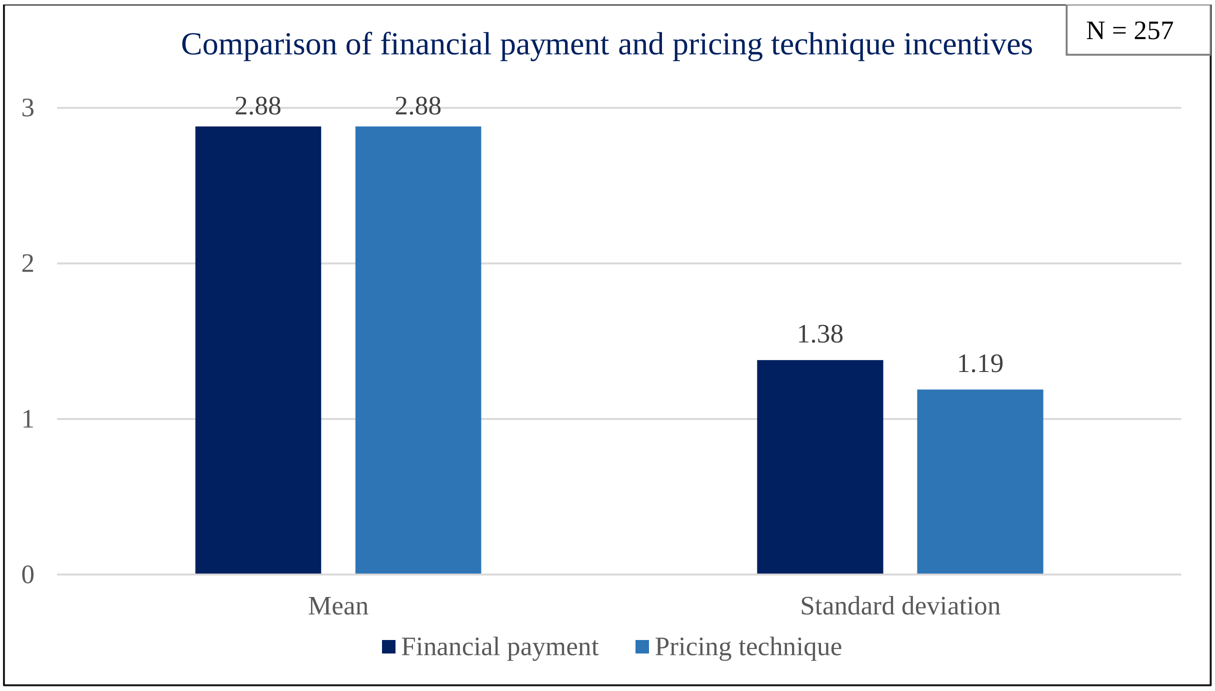


Figure 19: Comparison of the financial payment and pricing technique group (Source: Own creation)

As both groups were scored accurately equally, no difference in their effectiveness is presumed. To ensure this result, the Paired-sample t-Test is considered for the same reasons as in hypothesis 4. However, again no normal-distribution was found for these two variables. Hence, the comparison is made with the Wilcoxon Matched-Pairs Test. As expected, the p-value (0.872) scores above any common significance level, which indicates that there is no difference between financial payment and pricing technique incentives.

Therefore, hypothesis 5 is not supported. However, the difference within the group of non-monetary incentives has to be kept in mind. Incentives offering cheaper trips were scored lower than the option of free service. This will be further analyzed in 6.7. *Further analyses*.

6.6. Hypothesis 6

As hypotheses 4 and 5 focused on the differences in-between monetary and non-monetary incentives groups, this last hypothesis will compare the two big clusters. In line with this, hypothesis 6 states:

Monetary incentives will have a stronger effect on users' willingness to go to the suggested end-station than non-monetary incentives.

Incentive	Mean	Std. Deviation
Related	2.95	1.36
Non Related	2.71	1.02
Financial payment	2.88	1.38
Pricing technique	2.88	1.19
Monetary group	2.88	1.12
Non-monetary group	2.83	0.99

Table 7: Incentive groups (Source: Own creation)

The non-monetary incentive group is formed by non-related and related non-monetary incentives, while pricing techniques and financial payments are the basis for the monetary incentives. Like before an EFA is made on the basis of the already formed groups of financial payment, pricing technique and related non-monetary. However, as the group of related non-monetary incentives did not load properly, online incentives and the donation incentive are added separately to the analysis. All three assumptions of sampling adequacy (KMO Criterion = 0.69), sphericity (Bartlett's test is highly significant) and lack of multicollinearity (R matrix above 0.00001) are met. Again direct oblimin rotation and Kaiser Criterion were used. However, only one factor was found for which all of the variables loaded rather low (under 0.31). Nevertheless, a monetary and non-monetary group is formed to be able to test the current hypothesis. The means and standard deviations of these two groups as well as of the four former ones are stated in the previous table 7.

Graph 20 illustrates that the means are slightly different. As it was already seen in hypothesis 5, financial payment and pricing technique incentives have the same mean, which results in the same value of 2.88 for the monetary group. The non-monetary group is more diverse with two distinct means for the sub-groups. In total nonmonetary incentives were evaluated slightly lower on a value of 2.83. However, the standard deviation of the respondents' evaluation of monetary incentives is with 1.12 greater than the one of non-monetary ones (0.99). Hence, there was less variance in the evaluation of non-monetary incentives.

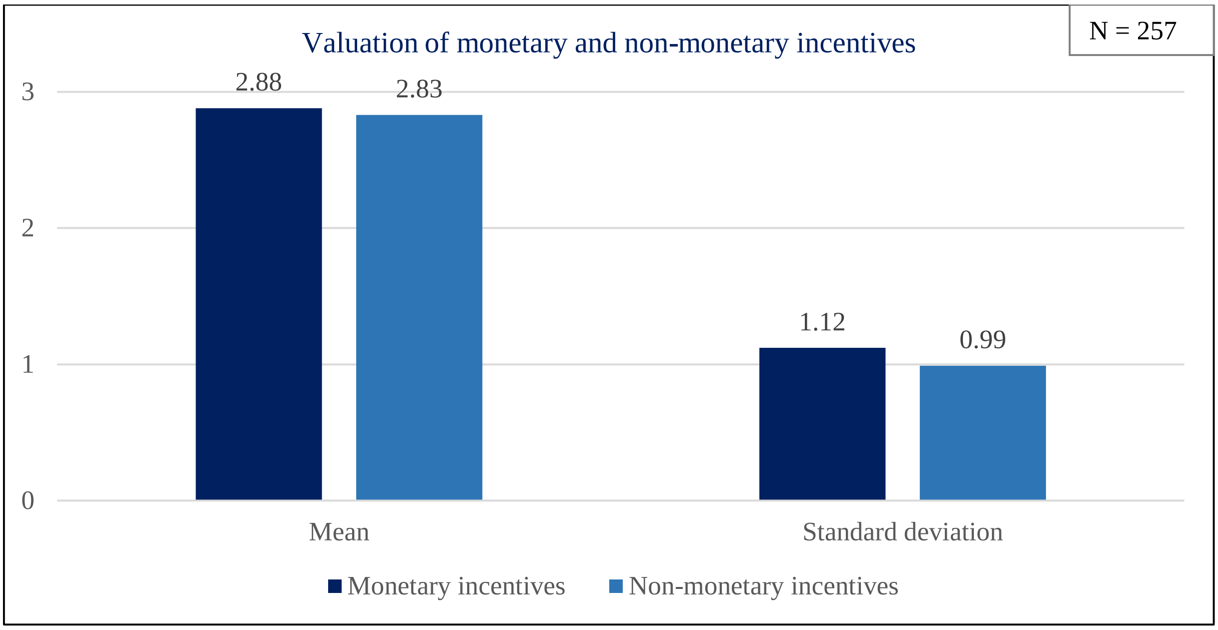


Figure 20: Comparison of monetary and non-monetary incentives (Source: Own creation)

Likewise to hypothesis 4 and 5, the Paired-sample t-Test is employed to compare these groups. By testing for the assumptions, it is found that the non-monetary incentive group is normally distributed at a significance level of 0.05. However, the KS-test for the monetary incentive group provided a value of 0.04, which is not significant for a level of 0.01, but significant if using a significance level of 0.05.

Therefore, first a significance level of 0.01 is assumed, which means that the normal distribution assumption is met for both variables. According to the Paired-sample t-Test no differences between monetary and non-monetary incentives is found (p-value > 0.05).

When employing a significance level of 0.05, the nonparametric Wilcoxon Matched-Pairs Test is employed due to the p-value of the KS-test of the monetary incentive group. Likewise to the

Paired-sample t-Test, it is not significant (p-value > 0.05) and, hence, does not indicate any significant differences.

As a result monetary incentives were slightly better evaluated than non-monetary incentives, but not significantly. Therefore, hypothesis 6 is not supported.

6.7. Further analyses

In the following, further analyses based on the gathered data set are made. Some of them were pointed out in context of hypotheses testing. Other further analyses are conducted to find further possible relationships between incentives effectiveness and personal, Citybike usage and/or demographic variables.

In order to test for any possible impact of the age on the effectiveness of the incentives, a simple regression is employed. The group which contains all offered incentives, hence, the incentive block except the general willingness variable, is tested together with the ratio variable age. A significant relationship (p-value = 0.005) is found. Beta is -0.02, which indicates that the willingness to follow the offered incentives declines with the age of the respondent. More precisely, each year a person ages, she/he is less willing to go to the suggested end-station by a factor of 0.02.

Likewise, it is tested for correlations between all ordinal data (usage frequency, average usage duration, sport frequency, donation behavior, both online behavior variables, occupation and income) and all incentives. The variable income is the only one being significant (p-value < 0.01). Hence, there is a relationship of the income level and the evaluation of the incentives. The more a person earns the less likely is she/he to pursue the offered incentive by a factor of 0.13.

As mentioned in hypothesis 4 the difference of the non-related non-monetary incentives will be analyzed. As all of the non-monetary incentives were measured with ratio data, a repeated measures ANOVA is used to compare them. First, it is tested for the assumptions of normal distribution and sphericity (equal variances of differences). By employing the Mauchly's Test and Kolmogorov Smirnov test it is found that the assumption of sphericity as well as of normal distribution are violated. Therefore, the non-parametric Friedman's Two-Way ANOVA is used to compare the non-related non-monetary incentives. The test is found to be highly significant (p-value = 0.000). Therefore, the respondents did significantly evaluate the non-related incentives differently. This means that the donation incentive is significantly evaluated at best (mean = 3.20), followed by the online coupon (mean = 2.55) and the online point system (mean = 2.39).

Furthermore, in hypothesis 5 a difference between the pricing technique incentives was found. The cheaper ones were lower evaluated than the one offering a free trip. Therefore, the Paired-sample t-Test is used to test for this comparison. First, a new variable which unites the two variables offering cheaper trips is created. Second, the assumption of normal distribution is checked and found violated. Therefore, the Wilcoxon Matched-Pairs Test is employed. It reveals that there is no difference in evaluation of the cheaper or for free incentives (p-value > 0.05).

As it could be seen in hypothesis 4 the EFA suggested a different grouping of the variables than needed for the hypothesis. Therefore, now the groups are formed according to the EFA outcome. This means that all related non-monetary incentives and the donation incentive are grouped. The second group is formed by the online non-related incentives: online coupon and point system for online platforms. All assumptions and values were discussed in the subchapter *Hypothesis 4* and are not repeated in this one. In order to compare these two groups the Paired-sample t-Test can be used. However, the assumption of normal distribution is not met. Therefore, the non-parametric test Wilcoxon Matched-Pairs test has to be employed. It was found to be highly significant, which means that the group of related incentives plus the donation one was evaluated significantly higher (mean = 3.01) than the online incentives (mean = 2.47).

Likewise to the previous point, in the subchapter *Hypothesis 6* the factor analysis yielded an interesting result by finding only one factor when running an EFA on all sub-groups. Therefore, a further EFA is conducted which includes all incentives individually. All three assumptions of sampling adequacy (KMO Criterion = 0.87), sphericity (Bartlett's test is highly significant) and lack of multicollinearity (R matrix above 0.00001) are met. Again direct oblimin rotation and Kaiser Criterion are employed and three factors are found. The first one is highly loaded (> 0.64) by all related non-monetary and pricing technique incentives. The second one consists of all financial payment incentives as well as the non-related donation and online coupon incentives (>0.56). The point system incentive is the only one loading highest on the third factor (0.87). However, it also loads (0.41) on the second factor, hence, above the common cut-off level of 0.4. Therefore, the incentives are grouped in the first two factors, putting the point system incentive in the second group.

Between these clusters a certain pattern of relation to the BSS can be found. While the non-monetary incentive group is already classified in related and non-related ones, the monetary cluster can also be divided by this factor. Pricing techniques are obviously related to the given system, while financial payment are unrelated. Therefore, the two new groups are called *generally related*, including related non-monetary incentives and pricing techniques, and *generally unrelated*, consisting of non-related non-monetary incentives and financial payment incentives. These groups can also be compared by using a Paired-sample t-Test. Although the assumption of normal distribution is met for the group of generally unrelated incentives, the generally related cluster violates it. Therefore, the non-parametric Wilcoxon Matched-Pairs test is again employed for comparison. It is found to be not significant. Even if the point system incentive is excluded from the *generally unrelated* incentive cluster, the result stays not significant. Therefore, no difference between generally related and generally unrelated incentives could be found.

7. Conclusion

In the following chapter and subchapters, the main outcomes of this master thesis are outlined. Therefore, research questions are answered and the main results are summarized. Furthermore, practical implication are given and limitations to the study at hand are pointed out. This is followed by a future outlook for potential studies and possible practical improvements.

7.1. Main results and answering the research questions

This subchapter deals with the results of hypotheses testing and the answers to the research questions. First, all hypotheses and their results are stated, then important outcomes of further analyses are given. In the second subchapter the research questions, which were drawn in the introduction, are answered based on the gathered information of literature and empirical research.

7.1.1. Main results

Hypothesis	Result
1: Incentives offered (monetary as well as non-monetary) will have a positive effect on users' willingness to go to the suggested end-station.	Supported
2: Donation as an incentive will have a stronger effect on users' willingness to go to the suggested end-station, if the user has donated at least once in the last year.	Not Supported
3: Online coupon bonuses as well as the point system for online platforms will have a stronger effect on users' willingness to go to the suggested end-station, if the user purchases online at least once a month or more often.	Not Supported
4: Related non-monetary incentives will have a stronger effect on users' willingness to go to the suggested end-station than non-related non-monetary incentives.	Supported
5: Financial payments will have a stronger effect on users' willingness to go to the suggested end-station than pricing techniques.	Not Supported
6: Monetary incentives will have a stronger effect on users' willingness to go to the suggested end-station than non-monetary incentives.	Not Supported

Table 8: Hypotheses (Source: Own creation)

The study this thesis has been based on has yielded numerous results. In table 8 all hypotheses and their outcomes are summarized. This shows that hypothesis 1 and 4 were supported, while in the case of all other hypotheses the null hypotheses were kept. Hence, the empirical research has found that offered incentives have an effect on the users' willingness to pursue the terminal's suggestions. Furthermore, the results show that related non-monetary incentives have a greater effect than non-related ones. In contrast, the effect of the donation incentive and online incentives (online coupon bonus and point system) do not depend on the respondent's donation and online behaviour. Furthermore, financial payments do not have greater influence on users than pricing techniques. Likewise, no significant difference of the impact of monetary and non-monetary incentives was found.

Apart from the elaborated hypotheses the data were tested for further influence of users' behaviour in the system, personal behaviour and demographic variables on the incentives effectiveness. It was found that the factors age and income have negative impact on the evaluation of incentives. The age of respondents has with 0.02 a rather small influence on the incentive's effectiveness. The income level of participants has with a beta of 0.13 more than six times a greater impact than age on incentives' evaluation. These numbers can be found in table 9.

Impact of	Beta	P-value
Age	-0.02	0.005
Income	-0.13	0.009

Table 9: Impacting factors on incentive effectiveness (Source: Own Figure)

Furthermore, significant difference in evaluation within the non-related non-monetary incentive group was found. This is not surprising as it is the most diverse group through being represented by three different incentives: donation, online coupon and online point system. Further analysis has shown that the donation incentive is significantly evaluated at best (mean = 3.20), followed by the online coupon (mean = 2.55) and the online point system (mean = 2.39).

Likewise, a significant difference between the cluster including the related non-monetary and the donation incentives and the group consisting of the online incentives has been found. With a mean of 3.01 the former group was evaluated higher by the respondents than the latter one, which scored a mean of 2.47.

7.1.2. Answering the research questions

In order to keep in line with the topic approached, research questions were elaborated in the introduction chapter. The whole thesis has then been built on the elaboration of answering them. In the following, short answers are given to each research question. For more detailed explanations the respective chapters of this master thesis have to be read.

Which reallocation methods exist for BSSs?

A literature review of existent reallocation techniques was conducted. These were divided into operator-based and agent-based ones and are described in detail in chapters 2 and 3. The operator-based reallocation methods were further characterized through a static or dynamic approach. In the case of static methods the demand of BSS is neglected. The main problems found in static reallocation techniques are finding upper and lower boundaries, solving the routing decision of the rebalancing trucks and calculating the optimal fleet size.

In case of dynamic methods the users' demand is taken into consideration and included in possible reallocation solutions. The focus of research on this kind of reallocation method lies on finding efficient performance measures and develop effective decision support systems for the system as well as accurate forecasting methods. For static and dynamic reallocation methods, simulations are run to get a better understanding of the dynamics of BSSs and the employed reallocation technique.

Furthermore, and the most interesting reallocation technique for the following research questions, are agent-based reallocation methods. This approach does not only include the systems' users in their solutions, but make them the main subject. Hence, different techniques have been elaborated how BSSs' users may balance the system. Two incentives are found to be practically employed in agent-based reallocation techniques: convenience fee and bonus time. In previous literature power of two choices, price techniques employed in end-station decision and price incentives used to alter total trip decisions are included. Moreover, potential incentives of research papers dealing with other topics than reallocation problems were extracted and discussed in chapter 4. *Incentives*.

Would users respond to incentives for changing their target location?

As mentioned in the previous research question, incentives are used in reallocation methods in BSSs. However, the users' willingness to pursue such offered incentives is a presumption for all of these approaches. Whether this presumption is met, was the first hypothesis dealing with empirical research. This hypothesis stated *Incentives offered (monetary as well as non-monetary) will have a positive effect on users' willingness to go to the suggested end station* and was found to be supported. Therefore, this second research question can be answered with yes, users would respond to incentives for changing their target location.

Which incentive(s) would be most effective for agent-based reallocation?

The donation incentive was found to be scored highest. Secondly, the bonus time incentives were evaluated at a high level. Furthermore, financial payment and the free trip incentives were some of the best valued options. Additionally, related incentives were found to be evaluated higher than non-related non-monetary ones. Hence, incentives which have a connection of some kind to the underlying BSS seem to be more effective than ones which do not.

Due to their high evaluation in regard to the respondents' willingness to go to the suggested end-station, these incentives are believed to be the most effective, when implemented in agent-based reallocation techniques

7.2. Practical implications, limitations and future outlook

In the following, practical implications of the outcomes, limitations to the study and a future outlook will be given. Practical implications are given in addition to the outcomes as they go beyond the result interpretations. Possible implications based on the yielded results will be listed and explained in the first part of this subchapter.

Secondly, limitations to the conducted survey are pointed out. It is important to keep all limitations in mind, as they might dilute the outcomes and it is not possible to have results, which are not subject to numerous limitations, from one survey. However, it is also pointed out, that the limitations only might have an impact on the results.

Finally, a theoretical and practical future outlook will be given. The theoretical future outlook will deal with potential studies on the topic approached. This suggested further research is believed to be missing at the current state of art and may add substantial value and knowledge to the problem at hand. Practical future outlook approaches real BSSs and the enhancement of their reallocation.

7.2.1. Practical implications

As it was described in the theoretical chapter about agent-based reallocation techniques, there are several distinct approaches and methods to apply user-based balancing methods. BSSs' operator may use these studies to evaluate different approaches of agent-based reallocations. There are differences in employing pricing techniques for end-station alteration or as a tool to alter the total trip decision. Furthermore, the power of two choices may be attractive for a PBS operator, but knowing advantages and disadvantages helps to implement them successful.

For these agent-based reallocation methods efficient incentives need to be chosen. The empirical study conducted has shown that donation incentives were evaluated at best by BSS users. Therefore, offering to donate two euros for a good cause leads users to pursue terminal's suggestions. Likewise, bonus time has been found to be an effective incentive. This one is already employed in Vélib's system and is seen to be rather easily implemented in a BSS. Donation incentives might be more complex, as each user may favour distinct subjects the money should be spent on. However, as it was evaluated at best and the incentive might be reinforced by the urge of people to act socially desirable, it should be taken into consideration.

Furthermore, when choosing an incentive for user-based balancing techniques, it should be kept in mind that related ones are more powerful than unrelated non-monetary incentives. Although the incentives had the same objective value, related non-monetary incentives, hence, bonus time was found to be more effective than the counter-group consisting of online incentives and donation. This might be as related incentives are perceived to be easier received and applied than ones, which are out of the system. However, it has to be kept in mind that donation incentives were significantly and substantially evaluated higher than the other two non-related non-monetary incentives. Therefore, if operators deal with the decision of choosing incentives, related ones should be favoured, except towards donation incentives.

Likewise to the previous point, discount points for online platforms might seem to be too complex, in terms of reception or honouring, for users to be attractive at the first look. Hence, introducing this kind of incentive at a later stage, when users are used to incentive schemes, or supplying substantial information might be necessary to use a point system as incentive effectively.

Eventually, it is suggested to take demographic data of the BSS's users in consideration when evaluating the option of a user-based balancing method. The results have shown that higher age and especially upper income levels hinder the effectiveness of incentives. Therefore, especially systems which are mainly used by younger people being in a lower salary bracket, should consider agent-based reallocation techniques.

7.2.2. Limitations

One of the most important limitations, which have to be kept in mind when reading this thesis, is that the study has not been made for Citybike users, but answered by them. This means that literature reviews and their approaches led to the questionnaire construction. Although some elements from the Citybike system in Vienna were included, the empirical research did not focus on improving merely this system. In contrast, the study was built to improve an abstract BSS through incentive based reallocation. Owing to these reasons some questions (i.e. the incentives of cheaper or free trips) were answered on an imaginary basis by the respondents. This is because, most respondents already use Citybike for free as Citybike offers its service for free up to one hour. As it was found in this study, more than 90% of the participants use Citybikes for less than an hour on average. Hence, the respondents had to think of a system, in which free or cheaper trips are an incentive. The same might be true for the related non-monetary incentives which were merely presented by bonus time.

Likewise, donation incentive, online coupon and online point system demanded the imaginary of the participants, as nothing like these incentives have been offered so far. Hence, this request for imaging the use of abstract incentives might be a limitation to the results of the research. However, most respondents had the chance to ask if they could not understand the sense of the questions through social networks, in which the questionnaire was posted, or by person.

One drawback of the results of hypotheses 4 and 6 are the formed groups. In order to test these hypotheses clusters had to be created. However, the conducted EFAs did show loadings which did not fit totally to the needed groups. Hence, they were formed although the included variables did not load properly. Therefore, some dilution to the results may have appeared. However, the proper groups, according to the loadings, were tested in sub-chapter 6.7. *Further analyses*. Hence, no results were lost.

Another potential limitation is the order of the incentive block. While all other questions in the questionnaire stated facts, the incentive block was based on opinion whether the respondent could imagine to respond to the offered incentive. Due to this quit intuitive way of answering these questions, the incentive block is rather vulnerable to satisfaction and relative evaluation. This means that incentives might have been evaluated differently due to the previously named incentives. An example for this give the financial payment incentives. Although all three items related with them, meant the same, this kind of incentive was evaluated less each time it occurred. As mentioned above, the first financial payment was the overall first incentive in the block and might have seemed rather attractive. However, by mentioning other incentives the evaluation was made in comparison to the other ones and declined heavily. Therefore, it has to be kept in mind that the respondents evaluated the incentives in comparisons to the other ones and not merely individual. This is a substantial limitation, as in case of implementing incentives, they are evaluated individually and not in comparison. This might result in distinct effectiveness.

7.2.3. Future outlook

The future outlook is divided into a theoretical and practical part. First, further theoretical approaches and studies are discussed, which would add substantial value to the topic at hand. Second, a future outlook for practice is given.

To further analyze agent-based reallocation methods theoretically, simulations to test outcomes, generating generalizable results and experimental testing are the main three future steps. First, the discussed outcomes from the conducted research may be implemented in a simulation to see their effect in an abstract BSS. Through this method the effect of the incentives can be further tested without implementing them in real world BSS, which might be rather complicating and time consuming.

Second, the outcomes pointed out are not generalizable as only respondents from one specific BSS were asked. PBS have different characteristics and distinct ways of operation. Furthermore, cultural differences due to regional differences have to be taken into consideration. Hence, further studies on the effectiveness of distinct incentives should be conducted in a variety of systems to yield results which are generalizable for all BSSs.

Thirdly, experimental testing is essential to check for the real effect of incentives. Respondents may not be able or willing to give accurate information in questionnaires. This is because imagining a certain situation is different from actual being in it. Furthermore, some attitudes are unconscious and, hence, cannot be expressed when being asked about them. Another problem with questionnaires is that participants may respond socially desirable, because they think a certain answer is expected. This socially desirability bias was tried to be avoided by not stating the problem in the description of the incentive block, however the results should be tested through a field study. This would add substantial value to their meaning and their real effectiveness could be ascertained.

In practice, the main future outlook is further implementation of agent-based reallocation techniques. As mentioned bonus time is already used in Vélib’s system, while the system of smart bike has implemented convenience fee as incentives. In future, other operators may follow their lead and introduce agent-based reallocation techniques for balanced and enhanced BSS performance.

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9. Appendix

Appendix 1: Questionnaire

Fragen zur CityBikes Nutzung

Wie häufig benutzen Sie CityBikes?
- □ Jeden Tag
- □ Mehrmals pro Woche
- □ Mehrmals im Monat
- □ Mehrmals im Jahr
- □ Seltener
- □ Nie

Haben Sie ein eigenes Fahrrad in Wien?
- □ Ja
- □ Nein

Sind Sie Tourist in Wien?
- □ Ja
- □ Nein

Wie lange benutzen Sie im Durchschnitt ein CityBike?
- □ Weniger als eine ½ Stunde
- □ ½ Stunde bis 1 Stunde
- □ 1 Stunde bis 2 Stunden
- □ 2 Stunden bis 3 Stunden
- □ 3 Stunden bis 4 Stunden
- □ Über 4 Stunden

Warum nutzen Sie CityBikes? (Mehrfachnennung ist möglich)
- □ Bequemlichkeit
- □ Umweltbewusstsein
- □ Kostengünstig
- □ Ergänzung zu öffentlichen Verkehrsmitteln
- □ Fitness
- □ Nahe der Arbeit
- □ Andere Gründe:_____________

Was schränkt Ihre Nutzung der CityBikes am meisten ein? (Mehrfachnennung ist möglich)
- □ Helmpflicht für Kinder
- □ Wetter (z.B. Regen, Kälte…)
- □ Fehlende Infrastruktur für Radfahrer (z.B. Radwege)
- □ Keine Citybike-Stationen in der Nähe
- □ Fehlende Citybikes bei versuchter Entnahme/ volle Stationen bei versuchter Rückgabe
- □ Kosten
- □ Länge der zu fahrenden Strecke
- □ Langsames Fortbewegungsmittel
- □ Andere Gründe:_____________

Stellen Sie sich bitte die folgende Situation vor: Sie kommen zu einer CityBike Station, um sich ein Fahrrad auszuborgen. Am Terminal werden Sie gebeten Ihre geplante Endstation einzugeben. Daraufhin werden Ihnen zusätzlich eine oder mehrere Stationen alternativ in einem Umkreis von max. 500 Metern zu Ihrer angegebenen Destination vorgeschlagen. Bitte geben Sie im folgenden Abschnitt an, ob und in welchem Fall/ in welchen Fällen Sie die (eine dieser) vorgeschlagene(n) Endstation(en) anfahren würden.

Ich würde zu der (eine der) vorgeschlagenen Endstation(en) fahren, wenn:	**Stimme überhaupt nicht zu**			**Stimme sehr zu**	
sie vom Terminal vorgeschlagen wird.	1	2	3	4	5
ich einen kleinen Geldbetrag von 2 Euro als Entschädigung bekomme.	1	2	3	4	5
im Gegenzug CityBike 2 Euro für einen guten Zweck spendet**.**	1	2	3	4	5
ich einen online Einkaufsgutschein im Wert von 2 Euro erhalte.	1	2	3	4	5
mir dafür 2 Euro gegeben werden würden.	1	2	3	4	5
ich 15 Minuten gratis Nutzung für zukünftige Fahrten bekomme.	1	2	3	4	5
ich für die vorgeschlagene Endstation weniger zahlen müsste als wenn ich zu der anfänglich gewählten Station fahren würde.	1	2	3	4	5
ich Extrazeit von 15 Minuten bekomme, die jederzeit eingesetzt werden kann.	1	2	3	4	5
die vorgeschlagene Fahrt billiger ist als wenn ich zu der ursprünglich geplanten Station fahren würde.	1	2	3	4	5
ich Bonuszeit von 15 Minuten bekomme.	1	2	3	4	5
ich nur für diese Station nichts zahlen müsste.	1	2	3	4	5
ich dafür Rabatt-Punkte, die auf verschiedenen online Plattformen einlösbar sind, bekomme.	1	2	3	4	5
eine monetäre Gegenleistung von 2 Euro gegeben ist.	1	2	3	4	5

Bitte beantworten Sie nun ein paar Fragen zu Ihrer Person

Wie oft betreiben Sie Sport?
- □ Täglich
- □ 4-6 mal/ Woche
- □ 1-3 mal/ Woche
- □ 1-3 mal/ Monat
- □ Seltener

Haben Sie selbst innerhalb der letzten 12 Monate in irgendeiner Form Geld gespendet?
- □ Ja, wöchentlich
- □ Ja, monatlich
- □ Ja, ab und zu
- □ Ja, zumindest einmal
- □ Nein, habe in den letzten 12 Monaten nicht gespendet

Wie oft sind Sie durchschnittlich online?
- □ Mehrmals täglich
- □ Mind. 1x pro Tag
- □ Mind. 1x pro Woche
- □ Mind. 1x pro Monat
- □ Mind. 1x im Quartal
- □ Mind. 1x pro Jahr
- □ Seltener

Wie oft kaufen Sie durchschnittlich online ein?
- □ Mehrmals täglich
- □ Mind. 1x pro Tag
- □ Mind. 1x pro Woche
- □ Mind. 1x pro Monat
- □ Mind. 1x im Quartal
- □ Mind. 1x pro Jahr
- □ Seltener

Sie sind…

□ männlich
□ weiblich

Wie alt sind Sie? ____

Leben Sie in einer…
□ städtischen Gegend
□ vorstädtischen Gegend
□ ländlichen Gegend

Was ist Ihre Tätigkeit?
□ Schüler(in)
□ Auszubildende(r)
□ Zivil-/Wehrdienst
□ Student(in)
□ Angestellte(r)/ Beamte(r)/ Arbeiter(in)
□ Selbstständige(r)
□ Hausfrau/-mann
□ Derzeit ohne Tätigkeit
□ Rentner(in)
□ Sonstiges: ________________________________

Wie hoch ist Ihr monatlich zur Verfügung stehendes Einkommen (netto)?*
□ Weniger als 500 Euro
□ 500 bis 1.500 Euro
□ 1.500 bis 3.000 Euro
□ 3.000 Euro und mehr

Vielen Dank für Ihre Teilnahme an der Befragung!

* Die Beantwortung dieser Frage ist optional.

Appendix 2: Abstracts

German abstract

Die unterliegende Masterarbeit beschäftigt sich mit Fahrradverleihsystemen und dessen Reallokation. Fahrräder solcher Verleihsysteme können bei jeder beliebigen Station ausgeborgt und zurückgegeben werden. Dies birgt einige Vorteile wie ständige Verfügbarkeit und schnelle Transportmöglichkeit für die Nutzer, allerdings auch den Nachteil der ungleichen Verteilung. Daher ist Reallokation in Fahrradverleihsystem essentiell, um die Versorgung sicherstellen zu können.

Die Reallokation durch die Betreiber und Mitarbeiter als auch durch die Nutzer wird in den Kapiteln 2 und 3 beschrieben. Dabei wird zwischen statischer und dynamischer Reallokation durch den Betreiber unterschieden. Die Nutzer basierende Verteilung wird durch die verschiedenen Anreizarten unterteilt. Weitere existierende Anreize und deren mögliche Einbindung in Reallokationsaktivitäten in Fahrradverleihsystemen, werden in Kapitel 4 erörtert. Im Zuge dieses Kapitels werden zwei Arten unterschieden: monetäre und nicht monetäre Anreize.

Basierend auf der Literaturrecherche über Reallokationsarten und Anreizsysteme, ist eine Umfrage erarbeitet und im CityBike System (ein Fahrradverleihsystem in Wien) durchgeführt worden. Von Mitte August bis Ende September 2014 wurde die Umfrage online und händisch unter CityBike Nutzern verteilt. Das Ziel der Befragung war es die Effizienz von Anreizen in Fahrradverleihsystemen zu prüfen. Speziell wurde der Einfluss von Anreizen auf die Bereitschaft von Nutzern, zu einer angegebenen Endstation zu fahren, eruiert. Weiters war es die Absicht, den effizientesten Anreiz zu finden und mögliche Einflüsse von System-relevanten und persönlichen Verhalten wie auch von demografischen Faktoren auf die Wirksamkeit von Anreizsystemen und einzelnen Anreizen zu evaluieren.

Die Studie mit 257 verwertbaren Antwortbögen ergab, dass Anreize einen positiven Einfluss auf die Bereitschaft der Nutzer haben, zu einer angegeben Station im Umkreis von maximal 500 Metern zu fahren. Weiters zeigte die Auswertung, dass eine versprochene Spende durch den Betreiber für einen guten Zweck, der am höchsten gewertete Anreiz ist. Grundsätzlich wurden Anreize zugehörig zum System signifikant höher gewertet als nichtzugehörige. Außerdem wurde ein negativer Effekt von steigendem Alter und Einkommen auf die Wirksamkeit der Anreize entdeckt.

Ebenfalls wichtig anzumerken ist, dass das Spende- sowie das online Verhalten der Nutzer keinen Einfluss auf die Wirkung von Anreizen durch Spenden, online Punktesystemen und online Gutscheine haben. Außerdem wurde kein signifikanter Unterschied zwischen des Effekts von monetären Auszahlungen und Preisnachlassen gefunden. Gleichermaßen wurden monetäre und nicht-monetäre Anreize gleich bewertet und es konnte keine signifikante Differenz zwischen diesen Hauptgruppen gefunden werden.

English abstract

This thesis aims to summarize the theoretical and practical state of art of reallocation in bike-sharing systems (BSSs) and the effectiveness of incentives in them. As the title suggests, the focus lies on the determination how incentives may be used in agent-based reallocation techniques and if they are effective. Incentives have hardly been employed practically to rebalance BSSs so far. However, several studies and simulations have been conducted to evaluate their effectiveness. Likewise, in this thesis the potential usage of incentives is analyzed and an empirical research is conducted to determine the potential influence of a variety of incentives in agent-based reallocation methods.

These incentives are divided into monetary and non-monetary incentives, which are further divided into four categories: financial payment and pricing techniques for the monetary incentives and non-related as well as related non-monetary rewards. The answering option for financial payment dealt merely with the reception of cash. Pricing techniques included free as well as cheaper rides. Related non-monetary incentives were given through granting bonus time. Online coupon, a point system for online platforms and donations presented non-related non-monetary incentives.

In the empirical research it was found that the donation incentive is scored highest by the respondents. Secondly, the bonus time incentives were evaluated at a high level. Furthermore, financial payment and the free trip incentives were some of the best valued options. Additionally, related incentives were found to be evaluated higher than non-related non-monetary ones. Hence, incentives which have a connection of some kind to the underlying BSS seem to be more effective than ones which do not. Due to their high evaluation in regard to the respondents’ willingness to go to the suggested end-station, these incentives are believed to be the most effective, when implemented in agent-based reallocation techniques.

Appendix 3: Curriculum Vitae

MARTINA ÜBERWIMMER, BSC

Date of birth	17.05.1990
Place of birth	Steyr, Austria
Nationality	Austria

Academic Education

Studies	Master Program of International Business Administration, Specialization in International Marketing
Dates	Since 10/2012
University	Faculty of Business, Economics and Statistics; University of Vienna
Studies	Exchange Semester
Dates	08/2011 – 12/2011
University	North Carolina State University, Raleigh, North Carolina, USA
Studies	Bachelor Program of International Business Administration, Specialization in Cross Functional Management
Dates	10/2008 – 08/2012
University	Vienna University of Economics and Business

Academic Practical Experience

Job description	Teaching assistant
Dates	10/2013 – 06/2014
Employer	Department of Innovation and Technology Management, Faculty of Business, Economics and Statistics, University of Vienna

Appendix 4: Statutory declaration

Ich erkläre hiermit an Eides statt, dass ich die vorliegende Arbeit selbstständig und ohne Benutzung anderer als der angegebenen Hilfsmittel angefertigt habe.

Die aus fremden Quellen direkt oder indirekt übernommenen Gedanken sind als solche kenntlich gemacht.

Die Arbeit wurde bisher in gleicher oder ähnlicher Form keiner anderen Prüfungsbehörde vorgelegt und auch noch nicht veröffentlicht.

Wien, am 09.02.2015

Martina Überwimmer, BSc