Covering the last mile

A study on bikesharing integration with public transportation in Oslo

Ellinor R. Anderson

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ABSTRACT

The rapid and global growth of bikesharing has come at a time when concerns for the environment are central in policy-making. It has, however, become apparent that the environmental benefits of bikesharing are at its best when bikesharing does not substitute walking, cycling or public transport and when it is combined with public transportation in covering the first and last mile of public transportation journeys. This thesis investigates how bikesharing is being integrated with public transportation in Oslo. To further understand the relationship between bikesharing and public transportation quantitative models were applied to address three knowledge gaps on the topic. Firstly, integrated use of public transportation and bikesharing on a trip-level tend to be the norm in studies. Results from this study show however that combined usage of public transportation and cycling in daily life is important in explaining membership choice. Secondly, previous studies usually view bikesharing members and non-members separately. Viewing these groups together has identified factors that affect interest in participating in bikesharing and factors that matter for actual membership. Findings suggest that environmental consciousness can explain interest in bikesharing, but membership choice is more likely to happen when urban characteristics and transportation in daily life makes it convenient. Finally, studies on integration between bikesharing and public transportation on trip-levels are often based on survey data or on bikesharing station frequencies. In this thesis it has been highly beneficial to use bikesharing population data on routes. Results indicate that bikesharing might serve an important integrational purpose with the metro- and railway- system in covering the first - and especially the last - mile of metro/railway journeys.

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The title of the thesis is “covering the last mile” and like bikesharing can be used to cover the last mile of a transportation journey the topic of bikesharing has been used to cover the last mile of my degree. This thesis would however never have come about had it not been for all the wonderful minds who have shared their time and knowledge on the topic with me. Gratitude goes out to all of you.

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1 INTRODUCTION

The pressing issues of climate change challenge how we conduct our lives as nearly all aspects of our current society contribute to greenhouse gas emissions. Transportation is one major source accounting for nearly a quarter of Europe's total greenhouse gas emissions and is the main cause of air pollution in cities (European commission, 2016). Reducing fossil fuel based travel is therefore crucial for both the local and global climate and has become a major policy objective for national- and city- governments across the globe (Moss, 2015).

Sharing our resources is viewed to be one solution to the over consumption of the world's resources, congestion and urban space issues and recent years have seen the emergence of a sharing economy (Frenken, 2017). The sharing economy allows services and goods to be shared amongst strangers and advances in the sharing economy have been especially apparent in cities as urban environments have proven to be beneficial for sharing (Munõs & Cohen, 2015). For the transportation sector it is argued that sharing mobility has the potential to make travel cheaper, cleaner and more accessible (Adams et.al, 2017). Innovations as well as participants within the field of shared mobility have been numerous; a development encouraged by many city governments.

One increasingly popular shared mobility service is bikesharing, and bikesharing systems have appeared in cities across the world as a green transportation measure (DeMaio, 2017; Mayer & Shaheen, 2017; Fishman, 2016). Bicycle sharing programmes serve as an alternative transportation mode in cities and provide public access to pick-up and drop-off bikes at numerous locations (Adams et.al., 2017). The potential environmental benefit of such programmes is however debated as a considerable number of trips are substituting other green transportation modes and the sustainable impact of bikesharing is argued to be limited (Fishman et.el. 2013).

It is however largely agreed upon that bikesharing systems in combination with public transportation can provide a low-carbon solution for the "last-mile" problem of a transportation journey without the need for a motorised vehicle (Liu, Z., et al., 2012). The "last-mile" problem is argued to be a major challenge in the public transportation system as using the transportation mode in itself requires some sort of travel. This challenge is one of the reasons why the private car is a comparatively efficient transportation mode since cars can provide door-to-door transport. Bikesharing may therefore serve an important role in access and egress trips to and from public transportation stops (- i.e cycling from a pick-up point to a metro station and / or vice versa). This can increase the competitiveness of the public transportation system as a whole.

Combining bikesharing with public transportation has thus been viewed important for sustainable travel and a new advance in shared mobility, mobility as a service may contribute to more easily combined transportation modes. Through smart phone technology, mobility as a service aims at facilitating door-to-door travel by integrating conventional forms of public transportation with shared mobility services (Jittrapirom et al., 2017). The emerging trend where accessing transportation modes is becoming relatively important compared to owning them, suggests that integrated transportation solutions will become more important in the near future. The new shift in trends, from ownership-based to access-based, point to the need for more research on integration between transportation modes (Frenken 2017). In this thesis, integration will be viewed from a user perspective on two different levels. Firstly, integrated use of the two systems may happen on a trip level in the form of access trips to public transportation and egress trips from public transportation to final destinations (Fishman et.al., 2013). Secondly, integration may happen in daily mobility as part of the different transportation modes individuals have access to and use in their day to day lives.

Bikesharing has long been considered a niche area, however because of its global reach and the proliferation of bikesharing schemes it be cannot be considered so anymore (Croci & Rossi, 2014). Despite its newfound relevance, research is lagging behind. Typical studies on bikesharing focus on their innovative aspects as well as how best to optimise the current systems (Shaheen, Guzman & Zhang et.al 2010, Pal & Zhang, 2017). Bikesharing integration with public transportation however is a field which has been somewhat neglected in current research.

Luckily, a few scholars have researched bikesharing in relation to public transportation systems (Fishman et.al 2013; Campbell & Brakewood 2017; Noland, Smart & Guo 2015; Martin & Shaheen, 2014). The main topic of these studies has been to what degree bikesharing is being used instead of unsustainable transportation modes such as private cars and taxis. These studies are usually quantitative in nature and typically find that bikesharing is substituting few trips from unsustainable transportation modes, and substituting many trips from sustainable transportation modes like public transportation and walking (Fishman et.al., 2013). The findings from the research is however not consistent, as some scholars argue that bikesharing is significantly contributing to sustainable travel (Martin & Shaheen, 2014).

In the current body of literature there are some knowledge gaps that I will address in the thesis. Firstly, research regarding who subscribe to bikesharing schemes tends to be based on surveys on bikesharing members (Fishman et.al, 2013; Martin & Shaheen, 2014). Only a few studies have collected data from non – members (e.g Efthymiou et.al., 2013). Comparison of data from members and non - members could be beneficial in discovering whether aspects related to public transportation are important factors in integrating bikesharing in daily life. This could identify which factors affect interest in bikesharing and distinguish those from factors that are important in taking the actual step to become a member. Such a comparison could also be beneficial to map the potential for upscaling the system.

Secondly, there are few, if any, studies that view bikesharing in relation to people's daily mobility patterns and transportation resources outside of bikesharing. The focus of previous literature on bikesharing members has mainly concerned itself with bikesharers' socio-economic and socio-demographic characteristics (Martin & Shaheen, 2014; Campbell & Brakewood, 2017; Fishman et.al, 2013; Guo et.al., 2017). Research on integration between bikesharing and public transportation in people's daily mobility is therefore necessary in order to fill this knowledge gap.

Finally, research regarding how bikesharing is integrated with public transportation on a trip level tend to either use survey data or data on bikesharing station frequencies and not routes between the stations (e.g Yang et.a., 2010; Noland et.al., 2016; Zhang et.al., 2017; Campbell & Brakewood, 2017). Station frequencies can be important to identify factors that increase use of a station, but in many ways, such a focus fails in explaining mobility patterns between the stations. An advantage would however be to focus on route frequencies between bikesharing stations to see if routes that are connected to public transportation at one end of the route positively correlates with higher user frequencies. Looking at the routes can thus indicate whether bikesharing is being used to cover the first and / or last mile of the journey.

1.1 AIM OF THE THESIS

This thesis is based on a theoretical framework informing about assumed causality on transportation behaviour generally, and on bikesharing behaviour specifically. Previous findings, which will be presented in a theoretical framework, form the basis for the rest of the thesis as hypothesis, and the choice of variables firmly rests on previous work on the topic. To address some of the knowledge gaps presented above this thesis will provide a comprehensive approach to bikesharing integration with public transportation. Two levels of integration will therefore be explored.

The analysis draws on data from multiple sources. A survey amongst bikesharing users and non-users based on the general population in Oslo and Bærum will be used to compare people who have a bikesharing membership with people who do not. The survey will be used to address bikesharing integration in daily mobility. Population data on bikesharing trips will be used to explore bikesharing mobility patterns and how this might be integrated into individual journeys. Various quantitative modelling techniques will be used to understand bikesharing integration with public transportation. The quantitative models are used to test hypothesis related to the topic and to discover correlations amongst the independent variables on dependent variables.

The main research question for the thesis is:

In what way and why is bikesharing being integrated with public transportation?

Some form of integration is expected as it is unlikely that the transportation modes are being used in total separation to bikesharing. Whether the integration is comprehensive or not, is however another question. The focus is therefore: why and how is integration happening? As the objective of the main research question is to understand integration in a comprehensive manner, it is necessary to unpack the question into two research questions linked to integration in daily life as well as in individual journeys. Answering the following questions can therefore contribute to further understanding the effect public transportation might have on bikesharing.

RQ 1: *How do daily- access and use of public transportation affect revealed bikesharing membership choice compared to stated interest in bikesharing participation?*

This question aims at addressing bikesharing integration in daily mobility. The majority of the respondents are not bikesharing members, but some are, forming a basis for comparison. The objective is to assess whether the respondents current mobility modes affect their interests in bikesharing schemes. By comparing the results, it is possible to find out if public transportation plays an important role for bikesharing integration in daily mobility.

Ordinal logit models will be used to see whether transportation resources and daily mobility patterns related to public transportation increases the likelihood of stated interest in participating in bikesharing programs. Binary logit models will be used with the same independent variables to see if they affect revealed membership choice.

RQ2 seeks to explore integration of bikesharing routes as port of individual public transportation journeys, either as access, egress or both.

RQ2: *What impact has connectivity to public transportation, along with other urban form aspects at bikesharing origin and destination stations, on bikesharing route frequencies?*

By answering this question, it is possible to gain insight into whether bikesharing is being used to access or egress public transportation. Proximity between public transportation and bikesharing station is used as an indicator for combined travel. However as other features at the bikesharing stations might be the real cause for route frequencies it is important to control for aspects known to impact ridership levels. Aspects known to impact bikesharing is urban form at start and end station as well as distance and elevation between stations (Liu et.al. 2012). In this thesis urban form is indicated by density, diversity, destination accessibility and distance to public transportation. If route frequencies are higher on routes that are connected to public transportation at one end of the route when controlling for the urban form at bikesharing stations, this can indicate that bikesharing is possibly used to access or egress public transportation. If this is the case bikesharing might play an important role in covering the first and last mile of a transportation journey. As mobility patterns change throughout the day, route frequencies during weekday morning and afternoon will be explored in addition to general frequencies.

The data used to answer this question is population data on bikesharing trips. This data has been joined with other spatial data that informs about the urban characteristics at the bikesharing stations as well as distance to public transportation. Negative binomial regression is used to measure the effect connectivity has on bikesharing route frequencies in general, as well as morning- and afternoon - frequencies.

By viewing key results from RQ1 and RQ2 together, bikesharing's role in relation to public transportation might be better understood.

1.2 THE CASE OF OSLO

The rationale for choosing Oslo is threefold: Firstly, literature on bikesharing has tended to have a limited focus on a few cities in the US, Great Britain, France, Australia and China (Fishman, 2016). As bikesharing may be related to factors like urban form, demography, economy, culture and climate, the current pool of literature is lacking studies from Northern Europe. Northern European cities are often distinct in that they have well-functioning public transportation systems, strong seasonal variation, and a high share of active modes like walking and cycling; a study from Oslo might therefore show a variety in bikesharing (Eurostat, 2018).

Secondly, Oslo is a city with ambitious environmental targets aiming at reducing greenhouse gas emissions by 50% within 2030 (Plansamarbeidet, 2015). Over half of the city's total emissions originate from transport, and policy objectives have therefore been directed towards the transportation sector. Halting car ownership in the Oslo region is viewed as one solution and sustainable transportation modes like public transportation, cycling and walking are supposed to account for any new growth in the transportation sector for the coming years (St. Meld. 33(2016-2017) p.147). As a consequence, sharing platforms like Oslo's bikesharing scheme have gained importance as a transportation mode in the city (St. Meld. 33(2016-2017) p. 76).

Finally, Oslo has had a bikesharing scheme since 2002 (Alsvik, 2009). The extent and membership numbers of the scheme "Oslo City Bike" has increased, especially in the latter years of its existence (Dagens næringsliv, 2018). Between 2015 to 2016 the subscriber number increased from 29 000 to 40 000 users (Regnskap og Økonomi, 2018). The program is currently gaining relevance as advances in the transportation company, "Ruter", is working towards more integrated travel solutions in the Oslo region; this includes bikesharing integration (Aarhaug 2017). The transportation company is taking a mobility as a service approach using smart phone technology to ease combined usage of public transportation in addition to shared mobility in order to promote sustainable mobility. The developments currently taking place in Oslo call for research on bikesharing integration with public transportation; this is a topic that has not yet been studied (Alsvik 2009; Bergström 2017; Langfeldt 2011). Furthermore a study from Oslo can add to the pool of international literature.

1.3 THESIS OUTLINE

In chapter 2 I will present a literature review on relevant research on the topics of shared mobility and bikesharing. Furthermore the theoretical framework will be presented here explaining relevant concepts and relationships between aspects that are related to bikesharing membership and bikesharing mobility patterns. There will be in particular a focus on integration between bikesharing and public transportation. Key concepts from *time geography* will also be presented in this section. Chapter 3 is the research design chapter. Here the study area, data and operationalisation of the theoretical concepts to quantifiable variables will be presented. An emphasis will be put on how data and methodological choices may impact the validity and reliability of this thesis. Also in this section the quantitative models will be presented and explained. Chapter 4 will deal with bikesharing integration with daily mobility and the results from RQ1 will be presented and discussed descriptively as well as analytically. Subsequently the results from RQ2 will be presented and modal integration will be discussed in chapter 5. This will first be done descriptively in maps before proceeding to the analytical results. The main findings from chapter 4 and chapter 5 will be viewed in relation to each other in order to answer the main RQ in chapter 6. The limitations of the thesis as well as further study will also be presented here.

2 THEORY

Bikesharing has been designated a specific role in sustainable travel, to cover the first and last mile of a public transportation journey (Liu et al., 2012). Whether bikesharing actually is used in this manner remains to be seen. To properly understand bikesharing integration with public transportation it is important to look to earlier research on the topic as well as looking to explanations regarding sustainable mobility. This body of literature forms the basis of the analytical framework which will be applied in this thesis.

The first section in the analytical framework seeks to explain bikesharing related travel behaviour, looking to the individuals using the system as well as the urban structures for an answer. Figuring out who bikesharers tend to be and what motivates such travel behaviour is viewed to be important for further analysis on bikesharing. Studies have also indicated that spatial structures, in terms of the urban form of an area, encourages certain types of travel behaviour, amongst others, bikesharing (e.g. Ewing & Cervero, 2010; Noland et.al. 2015; El-Assi et.al. 2017).

The next section of the analytical framework is dedicated to understanding mobility patterns from a time geographic perspective. Time and space impose opportunities as well as constraints on individuals' ability to travel (Hägesrstrand, 1985). I will argue that this perspective can enhance our understanding of bikesharing as it enables a more dynamic interpretation of the phenomenon. The first section of this chapter is however dedicated to the concept bikesharing and how this shared mobility service has developed from small scale idealistic initiatives to large scale sharing run by private operators (Martin & Shaheen, 2014). Literature from a Norwegian context will also be presented here.

2.1 BIKESHARING'S PLACE IN THE SHARING ECONOMY

"The Sharing Economy" was first conceptualised in 2008 and is argued to be among the most significant economic developments in the past decade (Puschmann & Alt, 2006, Frenken, 2017). The term was originally used to describe consumers granting each other temporary access to under-utilised goods (Frenken & Schor, 2017). The sharing economy has however undergone development since its emergence, as a significant number of businesses are taking part in the sharing economy. This trend has especially been apparent in shared mobility forms, such as bikesharing.

Even though sharing is something that has been going on throughout human existence, its present large and increasing scale and the fact that sharing is happening among strangers constitute important characteristics of the term sharing economy today (Frenken & Schor 2017). The sharing economy is in its most basic sense understood as consumers sharing physical artefacts in their usage (Frenken, 2017). One of the main characteristics of the sharing economy is that the consumer does not create a demand, but rather uses an under-utilized good, like a flat or a car. By lending or renting out under-utilized goods the consumer takes part in a positive-sum game, meaning that it is a win-win situation for both parts (Frenken, 2018).

A traditional characteristic of the sharing economy is a *consumer-to-consumer* (C2C) interaction, where the consumers grant each other temporary access, rather than giving another consumer permanent access, distinguishing it from second hand shopping where the consumer gets permanent access (Frenken & Schor, 2017). Digital platforms have been essential for the sharing economy because it can enable sharing between strangers by reducing the risk by rating systems. Even though strict definitions of sharing economy emphasize C2C interaction, the notion of sharing economy is often expanded to include other forms of interactions and increasingly *businesses to consumers* (B2C). This trend has especially become apparent after the commercialization of the sharing economy and the move from an ownership-based economy to an access based one.

As the sharing economy encompasses any under-utilized goods sharing mobility focuses on under-utilized transportation. Car sharing, ridesharing and public bikesharing are all forms of shared mobility which have been subject to recent research (Shaheen, 2016). Much of shared mobility has B2C interactions and this is especially the case for bikesharing. The B2C interactions are however increasingly used in combination with actors within the public transportation sector, a consequence of an emerging shift towards access-based transportation preference (Jittrapiron et.al, 2017). *Mobility as a service* (MaaS) is used to describe this shift in consumer preferences and MaaS is characterised by being flexible, personalised and on-demand (Aarhaug, 2017).

Similarly to the sharing economy the internet and other technologies are an essential part in its functioning. With that said MaaS extends well beyond shared mobility as important characteristics are service bundling, cooperativity and interconnectivity in transport modes and service providers (Jittrapiron et.al, 2017). This entails that car- and bike- sharing is part of a broader mix of transportation modes, often in cooperation with public transportation, where the user of the service pays one fee in order to access all transportation modes. MaaS aims for integrated solutions that enable door-to-door travel, eliminating the first and last mile problem, which will be discussed in more detail later.

The developments in the sharing economy suggest that it is taking on new forms, as not only businesses have entered the sharing economy, but that developments such as MaaS facilitates conventional forms of mobility to be combined with shared mobility.

2.2 BIKESHARING

Bikesharing systems have become an alternative low-emission and on-demand transportation mode in many cities (Parkes et.al. 2013). The concept “bike sharing systems” started in the mid 1960s as an idealistic initiative, but it is really only in the past decade that bikesharing is truly experiencing a rapid growth (Mateo-Babiano et.al, 2016). In 2016 bikesharing became a global phenomenon with around 2.3 million bikes available for the public on six continents (Demaio 2017). It is important to note that the rapid growth of bike sharing systems has come at a time where concerns for the environment, culture and health are central in policy-making, a trend which is also apparent in Oslo’s current policy making (Zhang et.al, 2015; Alsvik, 2009). The growth of bike sharing systems is therefore something that should not be viewed separately from broader political trends, especially so since many bikesharing schemes have been put in place as sustainability measures (Langfeldt 2011).

2.2.1 How bikesharing works

The principle behind bikesharing systems is simple; bikesharing users can access the bikes on an as-needed basis (Parkes et.al. 2013). The bikes are typically distributed on unattended stations in urban or dense areas where the users easily can pick-up and drop-off the public bikes. The fact that the stations are unattended, can be accessed beyond normal opening hours and managed at a large scale, separate them from ordinary bike rentals (Mateo-Babiano et.al, 2016). The past years have also seen an increase in dock-less bike sharing systems, especially in Asia

(The economist, 2017). A common trait is however that the user gains temporary access over the bike.

Bikesharing systems are normally distinguished by four generations connected to specific characteristics (Martin & Shaheen, 2014). Bike sharing started as an idealistic idea where anyone could access unlocked and free of charge bikes which were spread around the city. This is referred to as the first generation of bikesharing, which started in Amsterdam in 1965. White bikes were placed around the city, but the system did not last because of vandalism and theft of the bikes in addition to police officers removing the bikes from the street (Frade & Ribeiro, 2014). The second generation is the coin- or identification- deposit system. The most known example is from Copenhagen, where anyone who wanted to use the sharingbikes could insert a coin in order to access them. The system did not fully solve the theft and vandalism problem, but still operates some places in North America (Martin & Shaheen, 2014).

The third generation, which is most common today, is usually run by companies and uses information technology to operate the system and is incorporated into remote management of rental and payment systems. Smartphone apps can inform the users of bike availability, in addition the operators get a constant information flow of information on how the bikes should be distributed. Shaheen et.al (2010) also highlight the emergence of a fourth generation of bike sharing which is characterized by flexibility, clean docking stations, bicycle redistribution innovations, smart card integration and GPS technology and electric bikes. The IT based bike sharing system has also opened up for broader research on the topic, as crossing user data with movement data has become an alternative (Vogel et.al, 2014). This type of data can be used to study mobility behaviour at an individual level, an area which has only to a small degree been explored.

2.2.2 Existing literature on the Oslo City Bike scheme

To date there is a limited amount of literature on bikesharing systems in a Norwegian context, highlighting the need for more research on the topic, especially so because bikesharing is becoming a highly used transport mode in Oslo (Dagsavisen, 2018). Most of the knowledge which is available of Oslo’s bikesharing scheme come from previous master theses and newspaper articles. I will try to summarize their main findings.

The focus of Alsvik's (2009) master thesis lies on what the purpose of the Oslo bike sharing scheme was and why the scheme was adopted by elected officials. She highlights that even though many positive implementations of city bike schemes were mentioned by city officials, there were no clearly defined goal or expectations to the scheme before its implementation. She also argues that the bike sharing scheme in Oslo has functioned nearly as a trojan horse for the advertisement firm Clear Channel who gains advertisement access to desirable urban spaces. Bergström (2007) has also studied the impact advertisement funding has on the bikesharing system in Oslo and public-private partnership lies at the centre of the master thesis. His findings show that the funding model puts limits on the physical development of the system, in addition the outdoor advertisement affects the accessibility of other actors to use the outdoor media landscape.

Another master thesis which looks into the Oslo City Bike program is Langfeldt (2011), who has compared bikesharing programs in Barcelona, Bordeaux, London and Oslo in order to discover common features which indicate success of the bikesharing schemes. Langfeldt notes that the Oslo City Bike is not linked to a clear vision of sustainable mobility and increased mobility, compared to the other cities.

Earlier research on the Oslo City Bike has focused on players behind the program, city officials and private actors. There is therefore a large knowledge gap within the bike sharing literature in Oslo. There is little academic knowledge related to who the users are, and their socio-economic and demographic backgrounds and we know nothing about potential users among the general population. Furthermore, little focus has been dedicated to bikesharing and public transportation integration in Oslo, a topic increasingly covered in the international pool of literature. To what degree the bikesharing system in Oslo is being used in combination with public transportation to cover the last mile of a trip is therefore largely unknown.

Knowledge about ridership patterns in Oslo has to my knowledge not been published in any journals, even though a few newspaper articles and blogs have covered it. A highly read newspaper article by Aftenposten has for instance reported that most bikesharing trips in Oslo are going downhill (Aftenposten, 2016). Whether the travel pattern is mainly a consequence of a dislike of hills or other factors, like land use in the urban core and temporal patterns, is something which needs to be studied in more detail.

2.3 ANALYTICAL FRAMEWORK

Explaining bikesharing related travel behaviour

Travel behaviour ultimately rests on individuals' choices (Næss, 2015). There is however certain individual- and urban characteristics that are linked to using sustainable transportation which may help to explain bikesharing integration with public transportation (Næss, 2006). The next section therefore is dedicated to previous research seeking to explain who tend to use bikesharing systems and to what degree these are related to public transportation, what motivates the users and how much the urban form of an area may contribute to bikesharing.

2.3.1 The socio-economic and demographic background of bikesharers

In past studies socio-economic and demographic attributes have proven to be of great importance when analysing bikesharing (Fishman et.al., 2013). However, much of the earlier literature has not accounted for the users of the system and a majority of studies are based on internet surveys and smaller samples (Marleau et.al. 2012; Efthymiou et.al, 2013).

Literature on bikesharing point to some common membership characteristics. The largest group of bikesharers are generally in their mid-thirties, and the majority generally under the age of 40 years old (e.g. Martin & Shaheen, 2014; Campbell & Brakewood 2017; Fishman et.al, 2013). Furthermore bikesharers tend to be highly educated and often in high-income groups. Interestingly, a study by Shaheen et.al. (2011) found that the individual characteristics of bikesharers tend to be similar to that of *early adopters*. Early adopters are generally young and highly educated individuals who apply past practices and norms in new and innovative ways. Such individuals tend to be eager in learning about and adopting new products, such as bikesharing.

Male majority is also a common trait of bikesharing (Fishman et.al., 2015). Reasons for the male majority has been pointed out by Adams et.al (2017) who argue that a lack of infrastructure can explain why some women avoid bikesharing as women often have higher safety concerns. Furthermore women generally take on more responsibilities than men when it comes to daily duties as for example shopping and child care. Bikesharing might therefore not be an ideal transportation mode when transporting more than one person or when there is more than one mandatory activity on a journey. Gender may therefore impact ridership frequencies.

2.3.2 Bikesharers' transportation resources and daily mobility pattern

Studies on bikesharing members and their transportation resources have typically focused on ownership of the *transportation resources* car and bike. *Transportation resources* is a term commonly used to describe the ownership of, or accessibility to, different sources of mobility like private vehicles, bicycles, public transportation tickets and car- and bike-sharing memberships (Plevka et.al 2018). Few studies have to my knowledge had a specific focus on the relationship between access and use of public transportation in peoples' daily mobility and being a member of a bikesharing system (Bachand, Lee and El-Genedy, 2012).

Studies on bikesharers tend to find that they own their own bike, an unsurprising result as cyclists already have skill and habit of cycling and may also feel more confident travelling by bike (Fishman et.al. 2013; Adams et.al., 2017). Nuances however show that there are differences in their usage. A study comparing bikesharing mobility with cycling found that bikesharing bikes are used differently, as private bikes are often used for longer trips and exercise (Castillo-Manzano et.al 2016). Bikesharing bikes might also be used instead of a second bike, which are normally older and cheaper bikes or for one-way trips.

Even though there are limited studies that focus specifically on the impact of public transportation resources and mobility patterns on bikesharing membership, a few studies, such as Bachand-Marlau, Lee and El-Genedy (2012) do however include variables concerning travel patterns and access to public transportation. Their results show that using public transportation has a small, but significant effect on being a bikesharing member, whereas having a habit of combining cycling and public transportation greatly increases the likelihood of membership. The finding thus suggests that previous habits of intermodal travel is linked to integrating bikesharing with public transportation.

The relationship between the car as a transportation mode and bikesharing is however a topic that has gained more attention, as replacing car trips with bikesharing can have a considerable positive effect on the environment (Shaheen et.al., 2010). Yet studies usually find that bikesharing is negatively correlated with car ownership (Fishman, 2016). A study from China did however have different results as it found that car owners were more likely to be an early adopter of the bikesharing system (Shaheen et.al, 2011). Consistent findings were found in Canada, which showed that the likelihood of being a bikesharing member increased for people with a driver's licence (Bachand-Marlau, Lee and El-Genedy, 2012). Fishman et.al (2013) however argue that the relationship between car ownership and bikesharing membership may be unique to China, in which early adopters also were more willing to purchase a car. Furthermore access to a car may be a better measure for car usage than driver's license as there are more people with licenses than car access.

In terms of mobility patterns commuter trips are the most common trip purpose. Recreational trips are less frequent, but this varies between short term and long term members (Martin & Shaheen, 2014; Fishman, 2015). Not surprisingly bikesharing members report to use bikesharing for one-way trips, as the pick-up and drop-off functioning allows for a flexible mobility pattern.

2.3.3 Attitudes related to green travel

Attempts to change unsustainable travel behaviour has often been done trough campaigns trying to change individuals' attitudes (Prillwitz & Barr, 2011). However as there is an apparent mismatch between caring for the environment and sustainable behaviour, a body of research has tried to explain to what degree attitudes actually are affecting travel behaviour. The question thus becomes what motivates sustainable travel?

As argued above previous studies have found that bikesharers often are high income earners, which does not exclude them from being economically oriented. A question is whether the low prices of often heavily subsidised bikesharing schemes may be contributing to bikesharing participation. Not surprisingly, multiple studies find that economic incentives are related to using sustainable transportation modes (Gardner, 2009; Riggs, 2017). Efthymiou et.al (2013) found that the economically friendly prices of bikesharing schemes increased peoples' intention of becoming a member in the near future. Exploring this aspect further is therefore of interest, as it may impact the decision to become a member. Furthermore saving money has been stated as a motivational factor of becoming a bikesharing member (Fishman, 2016).

Pro-environmental attitudes or "green values" have in multiple studies shown to be correlated with more sustainable daily travel (Kahn & Morris 2009; Prillwitz & Barr, 2011). A study from Greece on intention to join a bikesharing programme for instance found that people who were environmentally conscious had a higher intention of joining a bikesharing scheme within a shorter time period than non-environmentally conscious people (Efthymiou et.al., 2013). Similarly Prillwitz & Barr (2011) found green consciousness to impact green travel behaviour.

Their study from the UK showed that green travellers often are young professionals living in urban areas who tend to vote for green parties. Compared to the other participants in the study this group walk and cycle more in their commuter trips.

Khan & Morris (2009) however argue that the consistency in earlier research on green travel behaviour and being environmentally conscious is low. Results from their own study showed that residents with high levels of pro-environmental beliefs cluster in high density areas close to city centres and rail transit, strongly suggesting that it is rather urban characteristics that promote green travel than attitudes. I will argue that this is in line with Prillwitz & Barr's (2011) study which also finds higher degrees of green travel by urban residents, further suggesting that it is urban living that is the real cause for sustainable travel.

Before presenting and discussing urban characteristics and how this is related to green transportation it is interesting to explore the idea that green travel might also be related to having an urban outlook in life. It has for a long time prevailed that there are some inherent differences between the urban and rural (McAndrews et.al, 2016). Some of these differences are physical like population density, industrialisation and a high variety of building functions and services (Næss, 2012). Other differences between the urban and rural are built on some common perceptions, for instance that rural lifestyles are simple and slow and even old fashioned. Urban lifestyles on the other hand are perceived to be fast, complicated and restless. There is of course much more to urban and rural lifestyles and any simple urban-rural dichotomy may conceal complexities in ways which may matter for transportation choice. Furthermore the car is more used in rural areas than in urban areas (Pucher & Renne, 2001). Rural dwellers, regardless of age and income rely on the private car for almost all travel needs. This has much to do with elements associated with low density like dispersed residences, activities and services which I will come back to later. With that said car ownership is closely linked to identity and maybe it is something about a rural identity which is closely connected with the private car (Hall, 2014)?

Bikesharing, which is nearly always found in urban settlements, may be linked to some sort of urban identity. This was suggested in Langfeldt's (2012) thesis who argues that bikesharing might be part of an urban identity as it is such a visible transportation mode in cities. Exploring this idea further to see if rural-urban preferences are linked to being interested in bikesharing participation as well as having a membership is therefore of interest. It is particularly interesting here, because the sample of this thesis does not only include the metropolitan area of Oslo, but also the neighbouring municipality, Bærum, where a higher mix of urban-rural preferences most likely will be found.

2.3.4 Urban form and travel behaviour – the five Ds

A highly studied area within urban planning is how the built environment may affect travel behaviour (Ewing & Cervero, 2010). Certain urban form characteristics has been linked to increased use of sustainable transportation like walking, cycling and public transportation. Moreover research related to bikesharing trip frequencies often look to the areas' urban form for answers (Noland et.al, 2016)

The urban form can thus play an essential role in explaining bikesharing usage and is commonly described by looking at five attributes, all starting with the letter D. Originally there were three Ds, *density, diversity and design* coined by Cervero & Kockleman (1997). Later *destination accessibility* and *distance to transit* was also added (Ewing & Cervero, 2010). These variables are known to say something about how the built environment affects travel.

Density, which is often measured as gross or net population, dwelling units, employment, etc, is known to affect travel behaviour. Denser cities are linked to lower levels of automobile travel, whereas in cities with low density there are tendencies to travel more by car (Hanssen, 2015). This pattern can also be seen on a smaller scale as people living in high-density neighbourhoods, such as the inner-city, are often less car dependent and use transportation modes like public transportation and bikes to a higher degree than those living in low-density neighbourhoods (Næss 2012, Williams, 2005). Density in Nordic cities contribute to reduced car travel, meaning that car travel is being substituted by other transportation modes like public transportation, walking and biking (Næss, 2012). The relationship between density and sustainable travel modes is therefore a reason why different measurements for density is nearly always included in studies of bikesharing patterns, as previous studies have at times found a strong relationship between dense areas and cycling (Zhang et.al., 2017).

Diversity, which is highly linked to density, measures the different land uses in a given area. A high mix of facilities reduces the need to travel far to access different facilities (Ewing & Cervero, 2010). A varied mix of facilities also become a destination in itself. Travel behaviour is especially influenced by the location of residence in relation to a concentration of facilities, rather than the distance to the closest facility (Næss, 2012). Where people live in relation to areas with high diversity is therefore an important indicator of travel behaviour. For bikesharing complementary land use like residential and retail can potentially function both as origin and destination for bikesharing users, increasing the use of stations placed in such areas (Mateo-Babiano et.al, 2016). Diversity is therefore something that is related to ridership frequencies.

Design is a measure of the street network characteristic within an area. Some network characteristics promote walking and cycling whereas others discourage it. Grid shaped networks for example encourage walking as the street network offers direct routes in most networks (Ewing & Cervero, 2010). This is however an aspect of urban form I will not delve too deeply into in the thesis.

Destination accessibility says something about the cost or ease it takes for people to get to their destinations (Ewing & Cervero, 2010). A common indicator for destination accessibility has been the distance to the city centre where there is a higher concentration of facilities. Short distances to the city centre are often linked to increased cycling and walkability, whereas longer distances are linked to increased used of motorised vehicles (Næss, 2006). Accessibility to the city centre can also be linked to bikesharing stations which in most cases are confined to inner city areas.

Distance to transit is commonly measured as the shortest route from a residence or workplace to the nearest public transportation stop (Ewing & Cervero, 2010). The distance says something about the use of public transportation. Earlier research has found that when the distance to public transportation is under 400 meters the transportation mode will generally be used more frequently than if the distance to public transportation is longer (Iacobucci, et al., 2017). This varies however, depending on the transportation mode. A study from Oslo and Akershus shows that people are willing to walk further for high efficiency transportation modes like metro and railway than to for example bus and trams (Ellis et.al.,2018).

An interesting aspect of distance to public transportation is that it might not only impact the use of public transportation, but also which mode people use as access and egress on their way to and from public transportation (Throndsen, 2017). Bikesharing might only be used in combination with public transportation if a bikesharing station is placed near the public transportation stop. Distance to public transportation has been used in a number of studies explaining bikesharing ridership levels, as bikesharing and public transportation have increasingly been viewed together (Bauchand-Marleau & El-Geneidy, 2012). I will discuss this relationship in further detail later.

2.3.5 Urban form and travel behaviour, is it so simple?

The argument above indicates a causal relationship where the urban form impacts travel behaviour. High-density areas encourage walking and cycling and low-density areas encourage the use of motorised vehicles. The causal relationship may however not be so simple, as individuals' residential preferences might be the real underlying cause for such travel behaviour (Næss, 2014). This phenomenon is called residential self-selection, and raises the question that maybe people are inherently different from each other and this is the real reason for choosing residential location. This can be exemplified with the conclusion from Morris and Khan's (2008) research presented above. Their study found that people with environmental preferences, who may want to live a certain lifestyle, to a larger degree clustered in inner city neighbourhoods. It might therefore be their desire to travel sustainably that cause their choice of residence and subsequently transportation behaviour. As Holden & Nordland (2005), however argues it is the urban form of the area which easier facilitates sustainable transport.

The issue of self-selection becomes problematic in quantitative regression models for two reasons. Firstly, because the independent variables are supposed to be independent of each other (Field, 2018). Secondly, the self-selection can function as an underlying third variable, where preference is the real underlying cause of the changes seen in the dependent variable, an aspect I will come back to later. It is however somewhat doubtful that people move to specific locations because they want to use bikesharing systems. With that said it is thinkable that people with urban or environmental attitudes move to avoid using a car, and bikesharing being amongst other transportation modes that they may chose.

I will argue that a similar logic of self-selection can also be applied to the location of the bikesharing stations. The locations of the stations are not random, as the locations are carefully planned in order to create a well-functioning transportation system (Jaffe, 2011). This suggests that bikesharing stations may be built with an intention to increase route frequencies. Stations are for instance located in areas that are in proximity to important destinations as well as being built in proximity to transportation hubs. Route frequencies, the dependent variable for RQ2, may therefore partially be a result of how the bikesharing system is planned. If the bikesharing system is planned as a consequence of demand, this will not be a problem for the thesis, as demand is likely related to the urban form of the area. If the supply on the other hand dictates the demand, self-selection becomes a problem for the analysis.

Another underlying factor which can impact the planning of bikesharing schemes and subsequently this thesis is advertisement at bikesharing stations. The Oslo City Bike, like many other bikesharing schemes are partially funded by advertisement placed at bikesharing stations (Aftenposten, 2014). It is possible that station locations are partially chosen with advertisement in mind, consequently advertisement exposure might be an underlying cause for bikesharing behaviour. If this is the case, the distribution of bikesharing stations might be located unevenly in places where people with purchasing power can be exposed for advertisement (Alsvik, 2009). It is however somewhat improbable that advertisement is the main factor behind station locations in its whole. As argued above bikesharing is related to density, diversity and destination accessibility, a type of urban form which is probably also beneficial for advertisement too.

With that said it is difficult to plan for how thousands of routes may be cycled and I will thus not be too concerned with the issue of self-selection presented above, though it is important to elaborate on as well as keeping such issue in mind. This discussion has however highlighted that the causal relationship between urban form and travel behaviour may not be as simple as first presented.

2.3.6 Understanding bikesharing mobility from a time geographic perspective

Stating the obvious, travel patterns change with time; during the day, season and decade. It is for instance a very different experience travelling at 11am compared to at the rush hour peak at 08am. It is therefore helpful to view travel behaviour through a concept that seeks to understand spatio-temporal mobility patterns. Time geography is an approach first developed by Torstein Hägerstrand and his associates, and central to the approach is that actions and events which constitute individuals' lives, always happen within the context of time and space (Pred, 1977). The main principles to the theory is:

" (1) that human life is temporally and spatially ordered; (2) that human life has both a physical and social dimension and (3) that the activities which constitute human life are limited by certain basic temporal and spatial constraints which condition various individual and group based activity possibility combinations" (Gregson, 1986, p.188).

The constraints that can steer the action and event sequence of an individuals' daily life are *capability-*, *coupling-* and *authority- constraints* (Pred, 1977). *Capability constraints* limit peoples' activity through their own physical, biological and cognitive capabilities like the need to sleep and eat. These physiological necessities limit the distance an individual can cover throughout any given time-span. Capability constraints like age can limit the distance a person is willing to bike or if the person is able cycle at all. This can for instance explain some of the demographic features of bikesharers, like the fact that most bikesharers are under the age of 40. In addition other physiological constraints like sweating or fatigue can limit certain routes or distances that people are willing to cycle, potentially saying something about people's mobility patterns. Capability constraints can help understand why attributes such as destination accessibility and distance to public transportation play such important roles when it comes to the choice of transportation mode.

Coupling constraints define when, where and for how long an individual must join other people or objects in order to form production, consumption, social, and various activity bundles. An example of a coupling constraint is to join other people at a work-place at a given time during the day. Consequentially this is impacting mobility patterns, as many people have the same coupling constraints linked to a nine to five job. The commuter pattern will in most cases put pressure on the public transportation system in form of cramp conditions on busses, trams, metros and railways in addition to queues on the roads. The distinct commuter pattern linked to coupling constraints also strains the bikesharing system as empty or full stations is common during rush hour depending on location.

Authority constraints on the other hand, are limitations imposed by regulations, laws, economics, such as the opening hours of bikesharing stations. An authority constraint imposed on bikesharing systems can be regulations regarding where to build bikesharing stations. If bikesharing is not a priority in urban planning the development of the transportation system can be limited, as stations are not gaining access to important areas where bikesharing might be used (Hägerstrand in Pred, 1977).

The resources, preferences and constraints of individuals are not context free, but linked to socio-demographics like age, gender, ethnicity and health issues. Socio-demographics may therefore affect individuals' preferences or function as mobility constraints (Dijst, 2013).

Constraints, preferences and resources are not static, but dynamic, meaning that the *possibility boundaries*, the paths available for individuals and groups to fulfil their projects will change with time and space (Gregory et.al. 1994). Students, with fewer resources, will for instance often have a different mobility pattern than a well established professional.

Hägerstrand (1985) points to the fact that human beings need to return to their home after shorter or longer excursions in order to rest, as one major constraint. It is only a limited time individuals can be away from their home before he/she needs to return. He calls this *the principal of return,* a principle that regulates and organises society as a whole (Hägerstrand, 1985). This impacts working hours, opening hours and the amount of time individuals can interact with others. Consequentially it also impacts how we travel, and can be used to understand different mobility patterns throughout a day.

How far an individual can travel during the timespan outside of the home, does vary. The *time space prism* approaches accessibility by incorporating spatial, temporal and transportation elements (Miller 1991). The prism represents the locations accessible for an individual, given the individual's mandatory activities in time and space, time budget and the travel velocity of his/her transportation mode. The space time prism is three-dimensional as shown in Figure 2.1. The *potential path space,* which is bounded by the space time prism, demonstrates the area an individual can access within a certain amount of time. The potential path space varies and is limited by constraints such as the number of duties an individual has throughout a day, his/her health situation as well as the transportation resources the individual has access to.

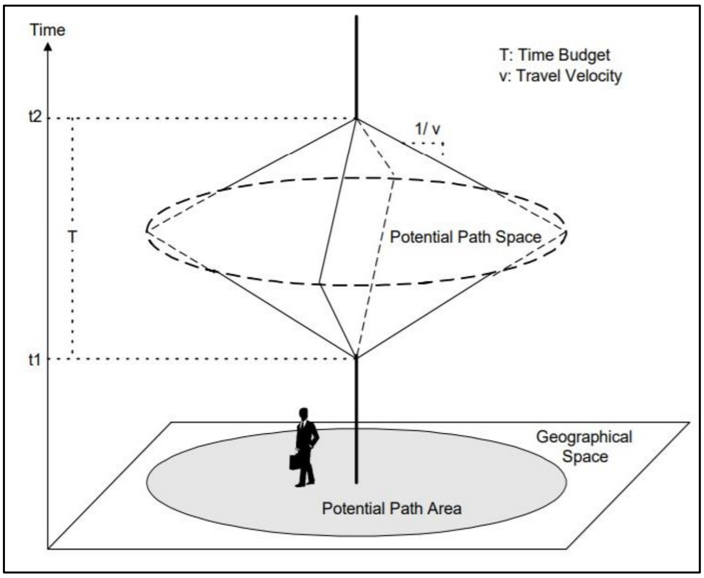

Figure 2.1:Time-space prism in Miller, 1991

The *potential path area* on the other hand represents the reachable area by the individual and signifies how large an area the individual can access within a certain time seen separate from daily duties etc. (Kwan, 2004). It is possible to increase an individual's time space prism as it is not static. Bikesharing can for example increase a person's time space prism as the transportation mode can increase an individuals geographical reach compared to walking.

The main critique of time geography comes mainly from a humanistic stance as time-geography has neglected human ideas, emotions and feelings (Gregson, 1986). In time-geography individuals' actions are mainly steered by the three constraints, disregarding autonomy to a certain degree. However, in some recent studies human emotions have been linked to time-geography and transportation studies (Dijst, 2013). Time geography can be approached qualitatively even though it has mainly been applied quantitatively (Pred, 1977). These are aspects of time geography which I am not capable of studying in the thesis, exemplifying the main point of time geography: time imposes limitations.

Another weakness which has been pointed out by Giddens (1984) is that time geography neither accounts for institutions and their transformations or power structures. Approaching bikesharing in Oslo with concepts from time geography definitely has its weaknesses. With that said it is beyond the scope of this thesis to study all aspects related to bikesharing systems. Moreover time geography is well suited to understand individuals' daily mobility patterns, activity choices and locations. Viewing for example urban form from a time geographic perspective can give us a better understanding of why distances play such a major role in peoples' mobility choices.

2.4 THE HYPOTHESIS: MODAL INTEGRATION VS MODAL SUBSTITUTION

As argued in the introduction of the chapter, integration with public transportation is viewed to be essential for sustainable transportation (Liu et.al., 2012). Fishman et.al (2013) have identified two relationships between bikesharing and public transportation; modal integration, where bikesharing systems are used in combination with public transport, and modal substitution, where trips which were previously taken by public transportation are now taken by bikesharing. These two relationships constitute a hypothesis for the analysis in the thesis.

2.4.1 Integration

Bikesharing combined with public transportation is viewed to play an especially important role for sustainable urban development. A humoristic saying about public transport is that “it takes you from where you are not, to where you do not want to be, on a vehicle on which you do not wish to ride” (Sagaris & Arora, 2016). The saying however highlights an important point; getting to and from public transportation does in itself require some sort of travel. This restriction can limit the use of public transportation as a travel mode for many urban dwellers and is viewed to be a major flaw in the transportation system. Bikesharing has increasingly been viewed as a solution to this inherent weakness of public transportation, as bikesharing can serve as a feeder mode for the first and last mile of transportation journeys. Combining bikesharing with other transport modes can potentially make public transportation and biking a more attractive option as it enables door-to-door transportation. The benefits are said to be flexible mobility, health benefits for individuals and societies and reduced congestion (Campbell & Brakewood, 2017; DeMaio, 2009; Griffin & Sener, 2016).

If the relationship to public transportation is modal integration, bikesharing can play an important role in access and egress trips. Bikesharing systems can be used to access (at the origin end of a trip) public transportation and/or egress (destination end of a trip) public transportation stops (Martens, 2007). Moreover, bikesharing has the potential to expand the access and/or egress reach compared to walking, changing individuals’ time-space boundaries.

The integration between bikesharing and public transportation is shown to be beneficial for both transportation modes (Ji et.al., 2018). New connections between bikesharing and public transportation has for instance increased the use of railway with 10% in Montreal (Martin & Shaheen, 2014). If this is purely a consequence of bikesharing is however somewhat uncertain. With that said other studies have also found that integration between bikesharing and efficient transportation modes like metro and railway has been especially beneficial. In Beijing and Hangzhou over half of the respondents of the bikesharing programmes are said to combine these transportation modes (Fishman et.al, 2013). Similar findings can be seen in Melbourne and Washington DC. The conclusions from these studies suggest that integration to the metro and railway system may be an especially important function of bikesharing programmes.

2.4.2 Substitution

Fishman et.al (2013) do however argue that the majority of scheme users are in fact substituting from other sustainable transportation modes like public transportation and walking rather than unsustainable modes like cars and taxis. This means that the environmental benefits of bikesharing might be exaggerated. A survey from China for example shows that around 80% of those using bikesharing systems would have walked, taken public transport or used their own bike if the scheme was not around (Tang, Pan & Shen, 2011). Studies from Manhattan and Brooklyn also support the modal substitution theory (Campbell & Brakewood, 2017; Noland, Smart & Guo, 2015). In Manhattan and Brooklyn there has been a reduction in bus ridership coincident with the implementation of the bikesharing systems in New York. Bus routes that are close to bikesharing stations are significant compared to routes that are not. Furthermore findings from Montreal and Washington DC show that bikesharing substitutes public transportation in dense areas, but in low-density environments the findings differ. There bikesharing establishes new connections to existing public transportation systems, suggesting that urban characteristics plays a significant role in how bikesharing is being used (Martin & Shaheen, 2014).

In addition there is also some scepticism to the role bikesharing can play in modal integration since bikesharing is in fact intermodal as it requires at least a short walk to and from bikesharing stations (Griffin & Sener, 2016). With that said bikesharing stations are often strategically scattered in close proximity to where people live, work, do their shopping, eat and where they relax. Also the bikes should be easy to pick up and drop off, meaning that there should not be too high time and energy cost using the bikesharing systems as a feeder mode compared to for example a private bike which also needs to be locked up somewhere.

From the current literature there is no clear agreement about model integration and modal substitution in addition to varying results on the environmental benefits of bikesharing. Martin and Shaheen (2014) in sharp contrast to Fishman, argue that findings from most cities with bikesharing programmes show that bikesharing has nearly universally reduced driving and taxi use (Martin & Shaheen, 2014). Zhang and Mi’s (2018) research from Shanghai supports such findings as bike sharing has reduced emissions in the city, especially in denser areas. They conclude that sharing mobility has the potential to reduce energy use and emissions in the transport sector as other transportation modes can be partially substituted by bicycles. To me the varying results suggest that the degree of integration varies from city to city, between urban form and context as well as being a result of different methods used to approach the issue.

Furthermore, bikesharing might also be used differently than both public transportation and walking. Biking compared to walking as a transportation mode for instance expands the access reach by 2 to 5 kilometres, a substantial distance. In addition cycling has nearly the same sustainability and health benefits as walking (Krizek & Stonebraker, 2010). Martens (2007) has argued that trips taken on bike will also often vary from those taken by foot or by public transport. Bike rides will often be longer than those taken by foot, but shorter than a public transport trip, consequentially bikesharing can play an important role for intermediary distances; distances that are too far for walking, but too short for competitive public transport, hence filling a gap that other transportation modes are not as capable of.

2.5 SUMMING UP

The sharing economy has become a growing phenomenon, especially so in cities. Sharing is happening to a greater extent than before and consumers as well as companies are participating in the sharing economy in various ways. Many city governments are now viewing shared mobility as part of the solution to urban and environmental problems like congestion and lack of space. From earlier literature we know that bikesharing can play an important role in covering the first and last mile of a transportation journey and the integration of the transportation modes has the potential to make public transportation more efficient. The research questions in this thesis are thus exploring integration with public transportation in Oslo.

How or whether people prefer using a bikesharing system may vary with capacity-, coupling-, and authority constraints. Factors such as age, distance and time will create various possibility boundaries. A time geographic perspective will therefore be fruitful as it enables a dynamic approach to the research questions. As the literature presented above has highlighted, the socio-economic and demographic constellation of individuals is related to mobility resources and daily mobility patterns. Resources, preferences and constraints of individuals are closely linked to their socio-demographic and socio-economic characteristics and these individual characteristics will therefore be controlled for in RQ1 when studying the relationship between people's mobility resources, mobility patterns and interest in bikesharing. Furthermore the literature suggests that key attitudes might also affect transportation behaviour and should thus be controlled for in the regression models.

It is argued from the literature above that urban form can impact mobility in cities. Different cities have their own unique urban form, and this may be why bikesharing systems have played such different roles in different cities. The urban from, especially the urban form in close proximity to bikesharing stations will most likely affect station- and route- frequencies. Dense and diverse areas have from previous studies been dominated by higher degrees of ridership levels than more remote areas. Such factors must therefore be controlled for when studying the relationship between stations in close proximity to public transportation and route frequencies, as the urban form of an area may be the real reason for high route frequencies. As travel patterns are dependent on time of day, especially during rush hours this is expected to be reflected in bikesharing mobility patterns. Such variations may also be explained from a time geographic perspective as time imposes different opportunities and constraints to the mobility patterns.

3 RESEARCH DESIGN

3.1 INTRODUCTION

Bikesharing integration with public transportation can be studied in a number of ways. Conducting detailed interviews with a limited number of bikesharing users with questions regarding bikesharing integration in their daily life could be one possible way to address this topic. Observing combined usage of bikesharing and metro rides at one bikesharing station could also be a way to address bikesharing integration in Oslo. These methods could have gathered detailed and in-depth information on the topic for a few individuals, but it would in many ways fail in giving a general picture of bikesharing integration in Oslo, which is the aim om this thesis.

Quantitative methods are therefore applied allowing statistically significant results from a smaller sample to be generalised to a larger population (Huff & Geis 1954). To what degree generalisation is possible however is reliant on valid and reliable data and modelling techniques. As error can occur throughout the whole research process it is important to address any shortcomings that may have arisen during the study as this can limit the ability to generalise findings. An important question to elaborate on is therefore how capable the smaller sample is in representing the whole population? If the sample is skewed, overrepresented or underrepresented by certain groups, the ability to generalise becomes limited (Bethlehem, 2010).

An ideal solution to this problem would be to have data on the whole population, eliminating the need for generalisation[1]. Statistical significance testing might seem somewhat unnecessary in such a situation, as the results build on the whole population (Rubin, 1985). With that said significance tests are essential if the aim of the research is to not only to describe differences in the population, but also linking the results to theoretical findings to address whether the independent variables help explain why there are differences in within the population. Significance testing is vital for this purpose, as it tests that any differences in the population is not a result by chance.

[1] The question, becomes however, is it possible to generalize findings to another population? This will be discussed in more detail further down.

Since the thesis builds on two different datasets, one dataset building on a sample and another dataset based on a population, they are linked to different challenges and opportunities and have therefore been handled in very different manners. Consequentially they will be presented separately in this chapter. The first dataset (Dataset 1) to be presented is a survey from the general population in Norway regarding willingness to use shared mobility services and will be used to address questions regarding integration of bikesharing in daily mobility. The second dataset (Dataset 2) deals with bikesharing trip population data and is used to analyse bikesharing mobility patterns in combination with public transportation in Oslo. I will therefore first present the data and operationalisation of variables linked to the shared mobility survey before addressing the same steps related to bikesharing trip data.

The last section of the chapter presents the multivariate modelling techniques which are used in the analysis. The models used in the thesis are in the same family of statistical models, *generalised linear models* (GLMs). Assumptions for GLMs will be addressed as well as presenting the subsequent models used to answer RQ1 and RQ2; ordinal logit regression, binary logit regression and negative binomial regression. First however the study area will be defined then the concepts validity and reliability will be presented, furthermore challenges regarding validity and reliability will be discussed throughout the chapter.

3.2 STUDY AREA

Scale is of major importance when studying anything which is geographic in nature. Scale, which is one of the fundaments in geography has acquired many meanings throughout time (Longeley et.al. 2015). It can say something about how fine scaled the data is. Scale is also related to the extent of the study area; the scale of the study area in other words has a great impact over the analytical results. For this thesis the extent of the study area has been highly dependent on two aspects; that the area has a substantial potential for bikesharing and public transportation integration, and access to relevant data.

There are currently 8 cities and towns in Norway with commercial bikesharing programmes, consequentially there are multiple options for studying this form of shared mobility in Norway (Langfeldt, 2011; Gobike, 2018; Tronstad, 2019). The reason Oslo is an especially fitting study area for bikesharing integration is the city’s combination of an established bikesharing scheme and a well-functioning transportation system (Hjorthol, Engebretsen & Uteng, 2014).

The study area in this thesis is therefore based on the area in which the Oslo City Bike operates and areas bikesharing subscribers might live. The study area of RQ2, dealing with bikesharing mobility patterns, is confined to the areas with bikesharing stations in Oslo. The study area is extended to the greater Oslo and the neighbouring municipality of Bærum where potential users of the system might live in order to address RQ1. The study area is presented in the map in Figure 3.1 and a point density map has been applied to demonstrate the number of survey respondents in the study area of Oslo and Bærum pr. km^2 in order to show where they live, whilst keeping their addresses anonymous. As the map illustrates, the majority of respondents live in immediate distance to the Oslo City Bike stations and thus have access to the bikesharing system. This strongly suggests that the survey respondents can be potential users of the scheme, a beneficial precondition for the analysis ahead.

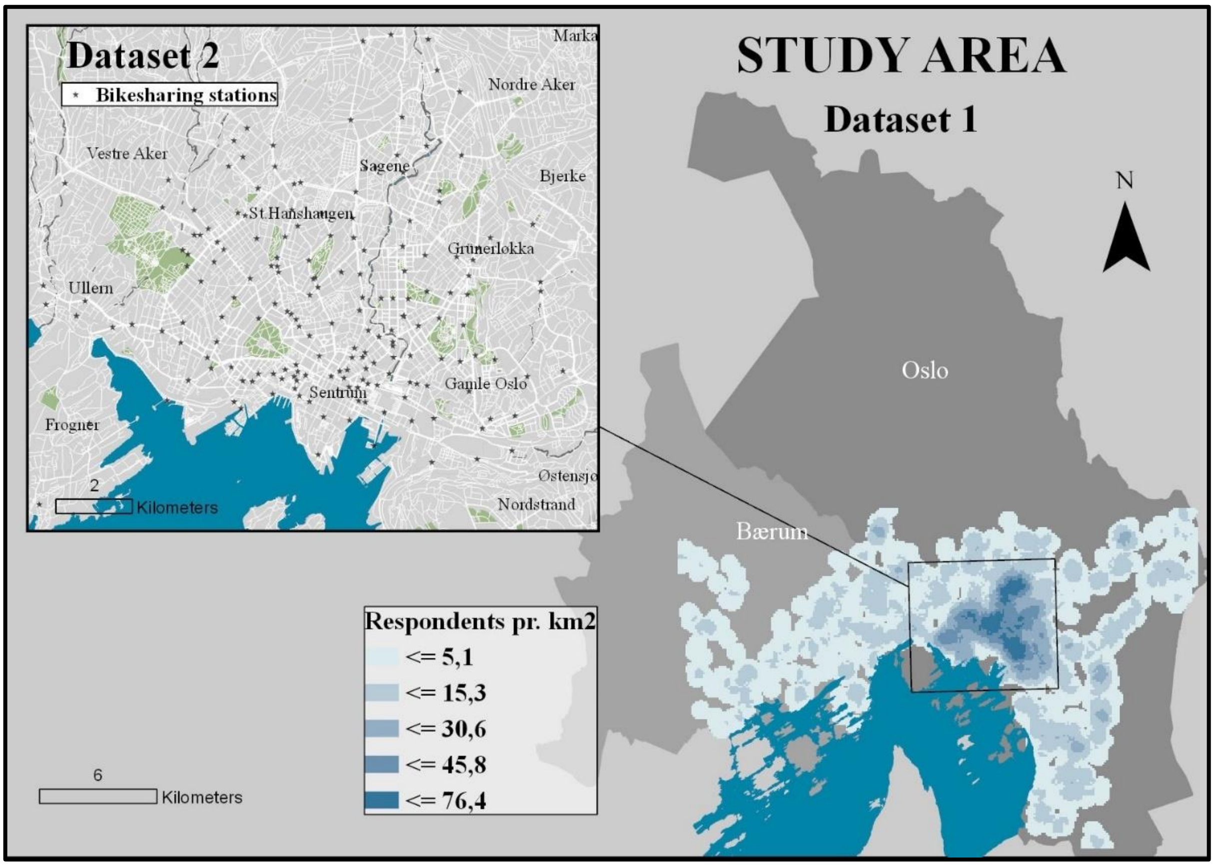

Figure 3.1: Map of the chosen study area for the thesis. Oslo and Bærum is the study area for RQ1. A density analysis is used to show the spatial dispersion of respondents. The extent of Oslo's bikesharing scheme is the study area for RQ2.

Oslo is the capital of Norway with the largest city population of 666 800 inhabitants in the country (SSB[a], 2019). Bærum is however also included in the analysis concerning bikesharing integration in daily mobility. Bærum is a municipality located to the west of Oslo with a population of 125 000 in 2017 and is included in the analysis for a number of reasons. Firstly, even though Bærum is a separate political entity, a high degree of cooperation between the municipalities is common, especially regarding transport related issues (Nasjonal transportplan, 2016). Efficient public transportation between the two areas is a high priority making travel between the areas easy and efficient. Secondly, about 20 percent of Bærum's inhabitants have a daily commute to Oslo, an indication that a substantial share of people living in Bærum is frequently using Oslo's transportation facilities (Akershus fylkeskommune, 2016). Thirdly, Bærum has its own bikesharing scheme that is run by the same operators as the Oslo City bike. Bærum's bikesharing scheme was however in its initial phase whilst the data collection took place, and studying access/egress trips to/from public transportation in Bærum is therefore not optimal considering the data (Svenningsen, 2016). In comparison studying potential bikesharing participants is highly interesting for this area as the bikesharing system is under development. Finally, Bærum had a relative large amount of survey respondents compared to other areas in close proximity to Oslo. A high number of respondents has been a necessary assumption for the regression models presented later in this chapter.

The study area for the analysis concerning modal integration (RQ2) is the extent of Oslo City Bike's stations as presented in the map in figure 3.1. The scheme had 184 bikesharing stations in the period 2016-2017, mainly located in the inner city in the areas of: Gamle Oslo, Grünerløkka, Sagene, St. Hanshaugen and Frogner in addition to a few bikesharing stations extending into the outer west and north of the city.

3.3 VALIDITY AND RELIABILITY

Errors can occur throughout the whole research process; from the early stages of data collection to the last analysis, and the concepts validity and reliability are used to discuss challenges regarding these errors and the trustworthiness of the research. The validity of research is reliant on measuring what it was intended to measure (Field, 2018). Imprecise operationalisation of theoretical concepts can for example in some cases lead to invalid conclusions as the variables are measuring something else than the phenomena it is claiming to analyse. In this thesis it is for example important to contemplate on how to best measure bikesharing integration with public transportation in daily mobility as well as in combined usage during trips. I will discuss this in more detail when presenting the variables.

External validity is related to the extent a study can be generalised to the population of the study area as well as to other populations, settings and time (Onwuegbuzie, 2000). External validity is therefore a concern for the degree results from the analysis can say about bikesharing integration in the whole population as well as in the not so distant future. Recalling the introduction of the chapter it is just as relevant to discuss the external validity of population data as sampling data. Here the question becomes if we can we expect to find the same type of results in the future or if the results from the population of Oslo be generalised to other contexts, to for example other Nordic cities. Degrees of caution should always be taken when generalising results (Longley et.al., 2011). With that said, this thesis assumes certain degrees of external validity from the literature it builds upon as concepts and variables are chosen with their results in mind. If similar results are found in this thesis it can suggest that the literature it builds on has external validity. Validity is necessary, but not sufficient in reducing error to a minimum. The reliability of the research must also be taken into consideration. The data is reliable if the same data is reused in another model and it gets the same results (Field, 2018). Contemplating and discussing the trustworthiness of the data, the variables and chosen statistical methods used in this thesis is therefore regarded important.

3.4 DATA

In the next section I will present data used to answer RQ1 and RQ2. Both of these datasets have however been merged with external statistics on grid cells from Statistics Norway regarding urban form. The first part of this section will therefore be dedicated to presenting grid the cell statistics, as well as discussing strengths and weaknesses of spatial joining. Thereafter Dataset 1 and Dataset 2 will be presented along with the operationalisation of theoretical concepts to measurable variables which will be used in the regression models.

3.4.1 The local neighbourhood - Statistics on grid cells

Statistics Norway, generally regarded to be a reliable source, provide a fine-grained standardised grid cell statistic covering Norway (Strand and Bloch, 2009). Each cell covers an area of 250m x 250m and the grid is linked to information on population, building mass, dwellings, employment and so forth. The small scale of the grid cells is beneficial for the analysis as it enables an investigation of smaller areas than for example political entities. Thus, the grid cells can eliminate the need to generalise characteristics of larger entities to smaller neighbourhoods, a problem termed *ecological fallacy* which can impact the validity of the results (Longley et.al., 2015). The main purpose of the grid cell is to define the local neighbourhood of the respondents in Dataset 1 and the bikesharing stations in Dataset 2 as characteristics of their neighbourhood can impact travel behaviour.

Since the data originates from different sources it needs to be viewed together. This can be achieved by spatial joining, a GIS-method used to join attributes from one table to another one based on the spatial relationship between the tables (Longley et.al. 2015). A clear advantage with spatial joining is that it enables the investigation of whether the spatial properties of a local neighbourhood effects individuals' behaviour. How the grid cells have been spatially joined with Dataset 1 and Dataset 2 differs and this has implications for how the local neighbourhood for RQ1 and RQ2 is defined.

In Dataset 1, which was provided to me through the *Shared Mobility for Innovative and Inclusive Green Cities* project (SHARMING*)*, the local neighbourhood is defined by the total land covered by 250m^2 cells that intersects a 300m radius from the x and y coordinates of the respondents' residences. In Dataset 2 the process of spatially joining the bikesharing station with grid cells involved creating buffers of 250m around the bikesharing stations in Oslo in order to extract spatial information from the area the bikesharing stations are located at. The buffer extracts the value from any grid cell it intersects and subsequently defines the local neighbourhood for the bikesharing stations.

With that said there are some problems associated with spatial joining, and m*odifiable areal unit problem* (MAUP) can be one source of statistical bias (Longley et.al. 2015). MAUP is related to how the size and shape of the areal units can influence the results. Two examples from Dataset 2 will be used to demonstrate how MAUP can have implications for the validity of the thesis. Firstly, defining the size of the local neighbourhood for bikesharing stations involved choosing a size that is large enough to capture factors that might impact the use of a bikesharing stations, but not so large that it extracts data that can be a source to ecological fallacy. This is especially important for bikesharing as earlier research has shown that people are not willing to walk too far to access a station, meaning that employment density is probably not directly influencing bikesharing station frequencies 1 km away to a substantial degree (Bauchand-Marleau & El-Geneidy, 2012). The chosen size of the local neighbourhood is therefore related to the results. This was to a certain degree accounted for by assessing buffers with different sizes in the regression models, and the best fit for the analysis pointed to buffers on 250m.

Secondly, as exemplified in Figure 3.2 the grid cells were not made to match the buffers used in Dataset 2, as the buffers not only take on the value of the cells that are placed nearly perfectly inside the buffers, but also cells that barely intersects them (Tollefsen, 2012). This becomes problematic as some buffers take on the values of nine grid cells whereas others take on the value of six grid cells – largely result of where the stations are located within the grid cells. Stations placed on the boarder of two grid cells will for example be intersecting fewer grid cells than stations that are located in the middle of a grid cell. The size and location of the grid cells compared to the bikesharing stations are therefore impacting the data and the validity of the thesis. This problem is however somewhat avoided by working with ratios, such as population density per area, and indexes instead of absolute sums.

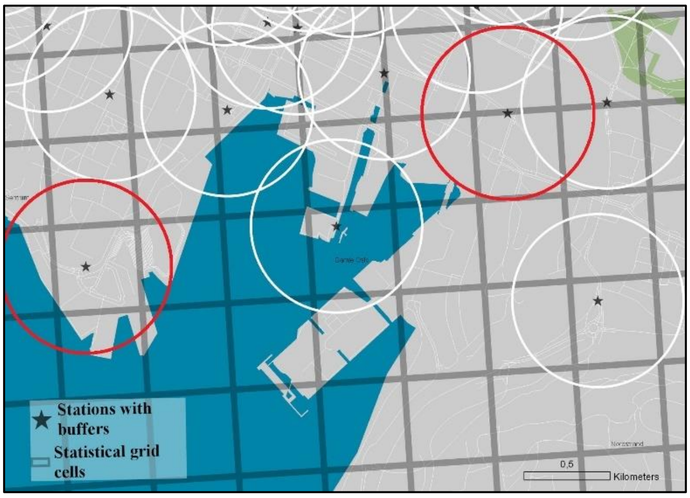

Figure 3.2: Map illustrating the inconsistent number of grid cells intersecting buffers on 250m, illustrating a MAUP. Source: SSB2017 and Kartverket2017

3.4.2 Dataset 1: Survey data

A survey on willingness to use shared mobility services was conducted by the *Institute of Transport Economics* and the *University of Oslo*. The survey was developed with the topic of my thesis in mind, meaning that many of the questions were tailored for the research's needs. This has been a clear advantage compared to having to use a more general survey on travel behaviour to answer RQ1. The questions were mainly concerned with mobility patterns, knowledge of shared mobility services and use of shared mobility as well as other transportation modes.

3.4.2.1 Data collection

"If you have a barrel of beans, some red and some white, there is only one way to find out precisely how many of each colour you have; Count 'em" (Huff & Geis, 1954:14).

An easier and less time consuming method to get the same results is to only pull out a handful of beans and only count them assuming that the proportion will be the same throughout the whole barrel. The same logic goes for statistical research, if the sample is large enough and selected properly, the sample can represent the whole population.

From statistical theory it is only purely random samples that can be examined with entire confidence (Huff & Geis, 1954). Essentially this means that it should be possible to generalise findings to the entire population of a study area based on results found in a small and random sample. The only problem is that completely random samples are difficult to achieve as some individuals and groups systematically eliminates or selects themselves for the survey making generalisation problematic.

Under-coverage and self-selection are two sources of selection bias (Bethlehem 2010). Under-coverage occurs when the selection mechanism is not able to reach certain groups of the target population (Bethlehem, 2010). Self-selection on the other hand occurs when individuals select themselves into the survey. Consequentially some groups of individuals are over-represented, whereas other groups are hardly accounted for in the study and the sample is not reflecting the population. The application of self-selection and under-coverage essentially means that the principles of probability samples are violated, and this process can thus lead to biased estimates.

Table 3.1: Responserate

	N	Percent
Opened e-mail	28 300	100
Opened link in e-mail	4622	16,3
Final response rate	3734	13,2

The survey was sent to randomly selected e-mails of people living in densely built areas in Norway. Everyone in the study area thus needed to have an e-mail, regular access to the internet and basic computer skills in order to have the same chance of being included in the sample. This can be a problem for the older population as they may not be as confident using the internet. Of the e-mails sent out 28 300 were opened, and these people could thus make an informed decision on whether they wanted to respond to the survey or not.

16 % opened the link to the survey whereas the total response rate was 13%. The survey included many questions which can explain why nearly 900 people did not complete it. The drop-out rate can cause sample bias and validity problems if the drop out is systematic

(Fincham, 2008). Self-selection may have occurred if a substantial amount of people interested in shared mobility answered the survey, whilst people who are not interested in the topic did not respond. The survey was therefore presented in a manner which anonymised the topic. Another source to self-selection that can have occurred from this sampling technique is if the survey was completed by another person in the household of the individual originally receiving the survey.

The dropout rate is as mentioned a national average. The drop-out rate for Oslo and Bærum is however unknown and it may be higher or lower than the national average. By comparing the sample to the study area it is possible to see to what degree they differ and whether the sample is representative.

3.4.2.2 Representativeness

The question is, can a sample of 1514 respondents represent Oslo and Bærum's population of nearly 800 000 (SSB 2019)? According to statistical theory this can be achieved by having a representative sample (Huff & Geiss, 1954). A sample is representative if everyone has the same chance of being included in the sample (Ringdal, 2013). As discussed this can be difficult to achieve because of aspects related to sample bias (Bethlehem 2010). The next section is therefore dedicated to examining the representativeness of the sample.

Table 3.2 compares some key characteristics between the population in Oslo and Bærum and the sample. The table shows that the sample is similar on certain aspects like area and gender. However the age and education distribution differ substantially on certain categories indicating sample skewness. Overrepresentation can be found in the age group 25-44 and highly educated people. This is however a common feature of survey samples as higher educated groups tend to have a higher response rate compared to lower educated groups (Curtin, Presser & Singer, 2000). With that said the population data is somewhat misleading, pointed out by Throndsen (2017), as Statistics Norway includes everyone over the age of 16 years

Table 3.2: Sample composition
Source: SSB 2019[A]

Sample N: 1514	Sample in %	Population in %
Area		
Oslo	86.5	84.3
Bærum	13.5	15.7
Age		
18-24 years	10.8	10.70
25-34 years	33.9	24.60
35-44 years	24.6	19.50
45-54 years	13.9	16.25
55-64 years	9.7	12.50
65 +	6.9	16.30
Gender		
Male	49.9	49.8
Education		
Primary education	2.6	20.4
High school	23.7	27.4
University up to 3 years	32.7	31.3
University, 5 years or more	41	20.9

old, giving a high proportion of the population with primary education as highest reached education in the population.

Underrepresentation is also found in the age group 55+, a similar problem in the national travel survey (Hjorthol, Engebretsen & Uteng, 2014). As argued above this may be due to the sampling technique, which require a certain degree of knowledge regarding computer and internet usage. In addition, by attending the survey the respondents could win an iPad. People who find this gift extra attractive could therefore have a higher chance of including themselves. Representativeness is high on certain areas, but the comparison between sample and population suggests that some degrees of caution should be taken in generalising results from the sample. Furthermore the representativeness of different ethnicities and income groups is not accounted for.

3.4.2.3 Operationalisation

Broad and socially constructed terms presented in the theory chapter need to be operationalised into quantifiable variables (Ringdal, 2013). The purpose of the analysis is to discover bikesharing integration in daily mobility, and to operationalise this concept to variables have subsequently been important. In the following section I will therefore present and elaborate on the operationalisation of key concepts like transportation resources and daily mobility patterns which can inform about daily mobility integration of bikesharing. However, because urban form, attitudes and demographics are known to impact travel behaviour, I will present variables that measure these concepts as they will later play a key role as control variables in the analysis.

3.4.2.3.1 The dependent variables - Stated interest in bikesharing participation and revealed membership choice

Stated interest in bikesharing participation is an ordinal dependent variable and the variable is used to see whether certain aspects of daily mobility are linked to higher degrees of interest in bikesharing. The variable builds on the survey question:

How interested would you be in using a bike from a bikesharing programme, if such a service existed in close proximity to where you live?[2]

Since the study area is confined to Oslo and Bærum nearly all respondents have access to a bikesharing bike, and the condition of proximity is met. There are seven different levels of interest the respondents could report varying from one, *not interested* to seven, *very interested*.

[2] My translation from Norwegian to English.

Table 3.4 presenting a summary of descriptive statistics tells that most respondents fall under the high and low categories of interest indicating that the variable is normally distributed.

Even though the question clearly asks how interested the respondents are in participating in a bikesharing programme, the variable may be measuring a more general perception towards bikesharing than actual intention in participating. This can impact the validity of the variable and certain caution will therefore be taken in the interpretation of the results presented in the next chapter (Onwuegbuzie, 2000).

The second dependent variable measures actually revealed membership choice. This variable is dichotomous and mutually exclusive as either the respondents have a membership or they do not. The validity of this question is therefore higher because it is measuring an actual outcome rather than a general statement. With that said membership does not necessarily mean that they are actively participating in bikesharing, a distinction which could have added to the analysis.

3.4.2.3.2 Independent variables - Access and use of public- and private- transportation modes

<u>*Daily mobility*</u>

Daily mobility pattern is an aggregation of travel behaviour in the study area and says something general about how people are travelling. Getting exact information over people's mobility pattern is an immense job requiring GPS observations. Subsequently it is impossible to get such detailed information through travel surveys. In traditional surveys daily mobility patterns are often defined by the distance, time and number of trips different transportation modes are being used during a certain time period (Ton et.al, 2019). In this thesis however the use and number of trips of transportation modes will be a proxy for daily mobility pattern. The information from the survey can add to a general picture of how people are travelling, but will be lacking explicit and detailed information.

The variable *Public transportation frequency* is an ordinal variable with eight different values measuring the weekly use of public transport throughout the past week. ranging from 0 times to 30 or more. A weakness of this variable is that it will be used as a continuous variable when the distance between the values are not equal. Even though this can impact the reliability of the variable it has been necessary due to model specifications and model fit.

I have also constructed a categorical variable, *Mobility mix*, measuring how cycling and public transportation is combined in the respondents' daily transportation mix. The subsequent categories are *Public transportation user*, *public transportation user and cyclist, cyclist* and *other*. *Public transportation user* is respondents who only reported to have travelled by public transportation during the past week. Public transportation user and cyclists have reported to have used both of these transportation modes during the past week. Cyclist have reported to only have cycled and in the category *other* are the respondents who have not reported to either having travelled by public transportation or cycled, most likely travelling by car or by foot. This variable gives a general picture of the daily mobility pattern of the survey respondents.

Transportation resources

Transportation resources is the ownership or accessibility to different sources of mobility like private vehicle, bicycle, public transportation ticket and car- and bike-sharing memberships (Plevka et.al 2018). Transportation resources is an important variable because ownership and usage is inter-related. Even though there is a variety of transportation resources, the variables *Access to car* and *Bike ownership* are included in the analysis. *Access to car* measures whether the respondent or someone in the respondent's household owns a car. *Bike ownership* is the ownership of any type of privately owned bike, not distinguishing whether it is an ordinary bike or an e-bike.

A weakness is that I do not have a variable containing information if the respondents have a public transportation card/app through the main travel company which operates in Oslo and Bærum. This weakness is however made up for by the variables measuring daily mobility patterns where multiple variables are measuring usage of the public transportation system. Together the variables measure daily mobility pattern and transportation resources used to indicate bikesharing integration in daily life through the variables' effect on stated interest in bikesharing participation and revealed membership choice.

The five Ds of urban form

Recalling chapter 2, *Density* has been important in explaining travel choice by bringing origin and destination closer together consequentially encouraging walking and cycling (Cervero & Kockelman 1997). P*opulation density* is frequently used to measure the density of an area and has in previous transport related literature proven to be an important explanatory variable and this measure is therefore also used in this thesis. Population density measures the aggregated number of people living within the local neighbourhood.

Building use diversity and density often coexist and some research has suggested that many of the benefits of density may actually be attributed to mixed land uses (Cervero & Kockelman 1997). It is therefore important to include a diversity measure in the models. *Diversity is* measured by the variable *Building use diversity* in the local neighbourhood and the variable was created from the grid cell statistics presented above. The cells inform about different building classes, like dwellings, offices, industrial buildings, educational buildings etc. When creating the variable, it has been important to look to the literature and include building functions which may promote bikesharing (Noland et.al., 2016). As bikesharing is used on smaller distances, areas with a mixture of dwellings, workplaces and services may promote bikesharing (Martens, 2007). The variable includes these building functions: dwellings, offices, industry buildings, restaurants and cultural venues and educational buildings. A weakness of the data pointed out by Throndsen (2017) is that buildings with mixed use are classified after the buildings' main purpose meaning that variety is lost. Furthermore the data do not inform about the intensity of activities in each building. This can impact the validity of the variable. The Shannon Wiener formula was used to measure building use diversity (Spellerberg & Fedor, 2003):

$$H = -\sum p_i \ln p_i$$

H is the natural logarithm of richness and P_i is the proportion of the building type relative to the total amount of building surrounding the residence of the respondents. A value of zero indicates that there is only one type of building use in the area, whereas higher index values indicate diverse building uses.

Destination accessibility could have been measured in a number of ways, for example as travel time or distance from residence to the city centre (Cervero & Kockelman, 1997). The categorical variable, *study area,* however is used to measure accessibility, and simply distinguishes between living in Oslo or Bærum, Oslo being a proxy for centrality being the capital city. One major weakness of this variable is that certain areas in Oslo are relatively more un-central than central areas in Bærum. With that said this issue applies for very few areas.

Access to public transportation is important in light of the research topic as bikesharing has often been viewed as a solution to the first and last mile problem of a public transportation journey. The variable *Logarithmic distance to public transportation* has been constructed. The original variable measured meters distance from respondents' residence to closest public transportation facility, using the natural logarithm of distance is however consistent with other mobility studies (Collantesa & Mokhtarianb, 2007). By transforming the variable, it measures the relative distance to public transportation. An increase from 1-2 meters will for example count considerably more than the increase from 210-211m. A weakness of this variable is that there is uncertainty linked to whether the closest public transportation facility is relevant for them. Nevertheless the variable can indicate connectivity.

Multicollinearity

As discussed in chapter 2 urban form characteristics are often linked to each other; highly populated areas will for example often be linked to building use diversity. Urban form is also known to be related to individuals' transportation resources as low-density areas are linked to car ownership (Williams, 2005). The correlation between these characteristics can cause havoc in the models in form of multicollinearity. Multicollinearity occurs when there is a strong correlation between two or more independent variables (Field, 2018). Three major problems can arise as a result of high collinearity. Firstly, collinearity can cause high standard errors of the coefficients and increases the chance of predictor equations that are unstable across samples reducing the reliability of the research. In addition the coefficients can become unrepresentative of those in the population. Secondly, multicollinearity can limit the size of the R^2 statistics and the model may be explaining more than the statistic suggests. Finally, multicollinearity between the independent variables make it difficult to assess the individual importance of the independent variables as the regression coefficients become interchangeable.

Tabele 3.3 Pearson's Correlation Matrix

Population density	1	.058*	-.382**	-.372**	-.386**	.067*
Building use mix	.058*	1	-.009	.028	.105**	-.071**
Bærum ref Oslo	-.382**	-.009	1	.200**	.219**	-.060*
Log. distance to PT	-.372**	.028	.200**	1	.177**	-.068*
Car access	-.386**	.105**	.219**	.177**	1	.112**
Bike ownership	-.067*	.071**	.060*	.068*	.112**	1

**p<0.01. *p <0.05.

Luckily low levels of collinearity pose little threat to the model estimates and a Pearson correlation matrix is used to check for high levels of correlation between individual urban form- and transportation resource- variables (Field, 2018). The estimates in the matrix can take any value from -1 to 1. Values close to 1 or -1 show signs of high correlation and will be removed as it causes multicollinearity in the regression analysis.

Table 3.3 shows that many of the variable correlate, especially population density and area, log. distance to PT and car access. The theoretical consideration of including population density in the analysis outweighs the potential problems that can arise with multicollinearity as the *persons r* values are not considerably strong. A *variance inflation factor* (VIF) test was also conducted in SPSS, with all variables included in the analysis. Similarly to the correlation matrix, the test indicates if an independent variable has a strong linear relationship to any of the other independent variables in the models. All VIF statistics were under the critical value of 5 (Field, 2018). Some caution should however be taken when discussing their individual effect on the dependent variable as there is some degree of interplay between the independent variables.

3.4.2.3.3 Controlling for - Individual characteristics and attitudes

<u>Individual characteristics</u>

Travel behaviour and resources are linked to individual characteristics like age, gender, affluence level, employment, norms, values, lifestyles and social obligations (Næss, 2012). It is therefore necessary to include variables which can control for these aspects. Some of these aspects are however easier to control for than others. I have therefore selected a few variables that say something about the socio-economic status and attitudes which may affect travel behaviour.

The variables' *gender*, *age*, *education* and *household income* are individual characteristics informing about the socio-economic status of the respondents. All of these variables except for age, are treated as dummy variables in the regression models. Education has two different categories, *higher* and *lower*. Higher education is anyone with three years or more at university or equivalent. Lower education are people who have primary education or just started higher education. The variable *household income* originally had 6 different categories varying from 250 000 NOK to 1. 5 million NOK or over. 8.3 percent did not want to report their household income resulting in some missing values. Different varieties have been assessed, first with all categories, then three categories and finally two as none of the varieties indicated an association between income and stated membership interest or revealed membership choice. Respondents with a household income of >1 000 000 NOK fall under the category *higher income* whereas the *lower income* group have a household income of < 999 999 NOK.

Attitudes

The variables *economic orientation, environmental consciousness* and *urban outlook* may impact bikesharing related travel behaviour and have thus been included in the model (McAndrews et.al 2016; Lanzini & Khan 2017; Fishman 2016). Economic orientation and environmental consciousness is built upon the respondents' mean score from multiple questions from the survey. For example there were five questions in the survey regarding environmental views, like being concerned about global warning, ensuring biodiversity, and reducing waste, all being on a scale from 1-7. Higher scores indicate a high level of environmental consciousness conversely are lower scores linked to being less environmentally conscious. The same was done for questions concerning being economically oriented. Urban outlook is only indicated by one question: *On a scale from rural to urban where would you most like to live?,* informing whether the respondents prefer an urban environment compared to a rural environment, regardless of where they live. A weakness is that individual measures of attitudes have a tendency to be inaccurate because they only derive a certain aspect of the attitudes' broader meaning, however by using the average of several other variables measuring various aspects of it this weakness can be somewhat avoided (ESS Edu Net, 2019).

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3.4.2.3.4 Variable summary table

Table 3.4 presents all variables included in the models and presents the data description and descriptive statistics.

	Descriptive statistics				Percent pr. category						
Variables	Min.	Max.	Mean	St.Div.	1	2	3	4	5	6	7
Stated membership interest (1=not interested - 7=very interested					21.3	8.7	8	14.4	14.5	8.1	25.1
Revealed membership choice (1= no membership. 2= membership)					85.8	14.2					
Individual characteristics											
Age	18	80	39.46	13.92							
Gender (1=female. 2=male)					50.5	49.5					
Education (1=lower. 2=higher)					26.4	73.6					
Household income (1= < 1 mill NOK. 2=> 1 mill NOK)					66.8	24.9					
Attitudes											
Economic orientation	1	7	5.38	1.12							
Environmental consciousness	1	7	5.12	1.38							
Urban outlook	1	7	4.99	1.66							
Transportation resources and urban form											
Population density	0	13263	3677	2682							
Building use diversity	0	1.59	1.15	.15							
Study area (1= Oslo. 2= Bærum)					86.5	13.5					
Distance to public transportation	0	1347	209.41	89.65							
Access to car (1= access. 2= no access)					60.8	39.2					
Bike ownership (1= owner. 2= not an owner)					24.5	75.5					
Daily mobility pattern											
Public transportation frequency (1=0. 2=1-3. 3= 4-6. 4= 7-10. 5=11-15. 6= 16-20. 7=21 +)					14.1	25.3	18.4	17.6	14.9	6.5	3.3
Public transportation user					59.2						
Public transportation user & cyclist					26.7						
Cyclist					4.2						
Other					9.9						

Table 3.4 Descriptive statistics of variables used to answer RQ1

3.4.3 Dataset 2: Bikesharing population data

As third generation bikesharing systems use IT-technology it has opened up for new opportunities for detailed research on mobility patterns on a larger scale (Vogel et.al, 2014). This is the case for the data on bikesharing trips that was acquired from *Urban Infrastructure Partner*, who runs the Oslo bikesharing scheme. Since the data is population-data and based on 4.5 million trips in the period 2016-2017 it means that bias related to sample data is avoided. Sample skewness and selection bias will therefore not be discussed in this section.

The data is used to answer RQ2, addressing bikesharing's role in access and egress trips to/ from public transportation in Oslo. Literature presented in the theory chapter strongly suggested that properties linked to the locations of bikesharing stations might be impacting ridership levels. And in order to answer the research question it has been necessary to transform the original dataset, by spatially joining other sources to it as well as transforming trip data into route data.

The dataset has as previously mentioned been spatially joined with statistical grid cells. Furthermore digital terrain models from *GeoNorge*, informing about the elevation in Oslo, has been spatially joined with the bikesharing stations. The spatial joining has provided information about urban form characteristics and altitude in the areas where the bikesharing stations are located. The next step of the data transformation has been to view the origin and destination stations together as part of a route. A routeID was therefore created from all start and end stations in the dataset, informing about all potential route combinations. In order to find out how many times the routes had been biked the route IDs were aggregated. In this way the dataset was transformed from 4.5 million trips to 34 040 routes informing about how many times each route has been subject to a trip[3].

3.4.3.1 Operationalisation

3.4.3.1.1 The dependent variables - Route frequencies

The dependent variables are based on count data and measures the bikesharing routes' frequency. The variables inform about all route combinations between start and end station and

[3] Routes that start and end at the same bikesharing station was excluded from the analysis as most of these trips were not round trips, but rather people returning bikes to the same stations because of malfunctions with the bikes.

how many times they have been cycled in the period between 2016-2017. The first variable is *route frequency* and measures the total amount of times all route combinations have been cycled at any given time during the running hours of the Oslo City Bike. *Route frequency* is a count variable because it is essentially informing about how many times an event has occurred (Cameron & Trivedi, 1998). The event of a route being cycled by a sharing bike occurs from 0 – 10 218 times. The variance is large, and some routes are highly favoured whereas others are non-existent. Consequently, this has led to a high variance, an implication for model choice, a topic I will come back to later.

In order to see spatio-temporal variations in the dependent variable two other count variables have been created. The choice of time was based on the graph in Figure 3.3 that shows the temporal variation in the dependent variable. There are two clear peaks with high route frequencies throughout a day, both with three-hour intervals which form the bases for *morning route frequency* and *afternoon route frequency*. *Morning route frequencies* measure routes' frequencies during the weekday morning peak from 06:00 to 09:00. The event that a route has been cycled during this time period varies here from 0 – 2249 times. The second variable is *afternoon route frequency* that measures the routes' frequency from 15:00 to 18:00. The afternoon routes' frequencies varies from 0-1431 times.

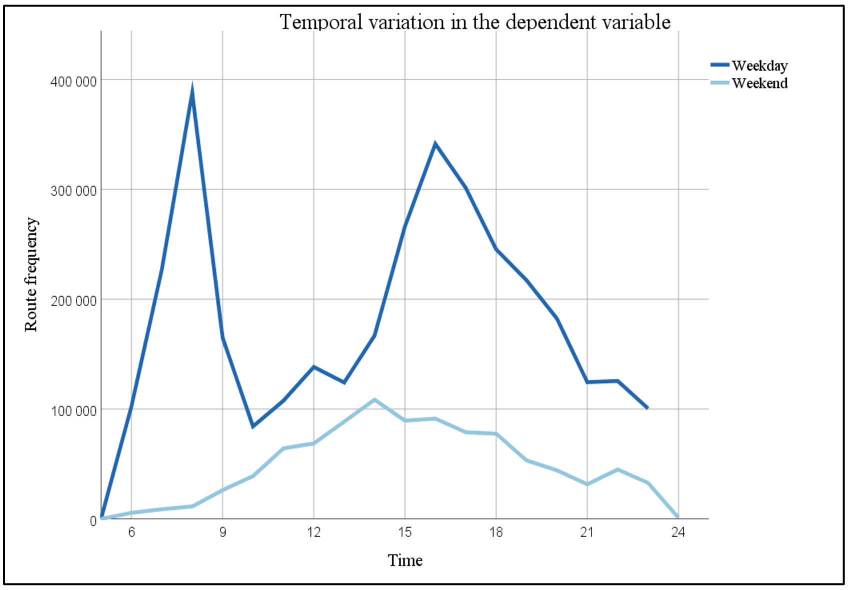


Figure 3.3: A line chart demonstrating temporal variations in route frequency during weekdays and weekends

The graph indicates that morning route frequencies essentially are informing about commuter trips as the sum of route frequencies is highest in a narrow time-frame around 08:00. Afternoon route frequency might inform about more varied trip purposes, as high route frequencies occur during a longer time spam.

3.4.3.1.2 Independent variables - Urban form

Similarly to Dataset 1 are variables related to density, diversity, distance to public transportation and destination accessibility used to answer RQ2. The urban form variables in Dataset 2 are however included in order to explain actual bikesharing mobility patterns. The station environments at the start and at the end of a route is expected to impact why the route was cycled, as we normally travel in order to access something at another location (Næss, 2006). Controlling for aspects which might generate a trip is therefore necessary in order to isolate the effect of being connected to public transportation.

As only start and end station is known the rest of the route becomes a guess. The best estimation for aggregated behaviour is that people tend to choose the shortest route between origin and destination. The weakness here is that other aspects which might also affect a route cannot be accounted for. For example, a route between two stations might be short, but if it is viewed unsafe it might be avoided (Hullberg et.al 2018). A consequence of this weakness is that variables concerning the urban form along the route will not be included in the regression models as the route builds on an assumption of shortest distance. Adding urban form characteristics that might impact route choice will therefore be counter intuitive.

Connectivity to metro/railway stations

Distance to public transportation is the urban form variable that is of most interest and is the test-variable used to answer RQ2. From earlier research we know that bikesharing plays an especially important role in access/egress trips to and from metro- and railway stations (Lansell, 2011; Ji et.al., 2018). The variable *connectivity to metro/railway station* was therefore created in order to test whether bikesharing shows similar signs of integration in Oslo.

An origin destination cost matrix analysis (OD cost matrix) was used to measure connectivity between bikesharing and metro/railway stations in ArcMap. The network analysis calculates the shortest route between two or more locations (Mitchell, 2012). Lowest cost in this analysis is the shortest distance between origin, bikesharing station and destination, metro/railway station. An advantage is that the distance is calculated over an OpenStreetMap network considering the road design between origin and destination.

The geographic location of metro/railway stations originates from GTFS9 data from "Ruter" and "NSB" (2016/2017). The data is on public transportation schedules and is associated with geographic locations. A weakness with this data, noted by Throndsen (2017), is that the geographical points of the stations are central locations along the railway infrastructure, and not entry points. It might however be more accurate to measure distance between entry point and bikesharing station.

Defining connectivity has been necessary as the chosen distance will impact the conclusion of the thesis. Earlier reports have shown that the distance most people are willing to walk to access public transportation is 400m and this number increases for access trips to metro and railway stations (Iacobucci et.al., 2017). With that said it is uncertainty linked to the distance people are willing to walk in order to access a bikesharing station. The distance may be considerably shorter as most bikesharing trips are of intermediary distances and a long walk to access a bike may be counter intuitive (Martens 2007). Keeping this in mind the maximum distance was set to 200m from bikesharing station to public transportation, a distance ensuring that geographical points of the metro/railway stations are within reach of the bikesharing stations in addition to being within a reasonable walking distance. Stations with =< 200m distance from bikesharing stations were selected to create the variable in SPSS.

The variable *Connectivity to metro/railway station,* has four different categories measuring different connectivity variations between bikesharing and metro/railway stations illustrated in Figure 3.4. The first two categories demonstrate routes that are connected to metro/railway stations at one end of the route representing trips that have the potential to function as access and/or egress trips to/from public transportation. The first combination is where there is no connectivity at origin station of the route, but it has access to

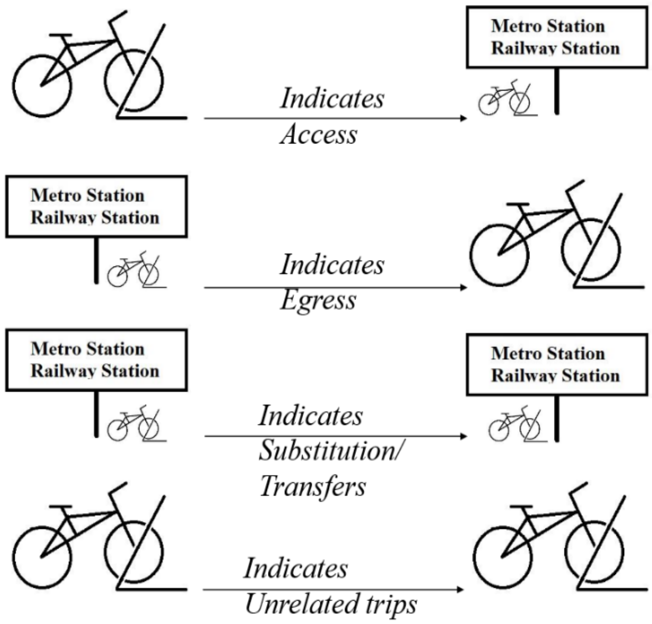


Figure 3.4: An illustration of connectivity variations between bikesharing stations and metro/railway stations.

metro/railway station at the destination end of the route. The second variation is where the origin bikesharing station is within 200m of a metro/railway station, but the destination bikesharing station is not connected. The third variation represent trips which may be substituting metro/railway journeys as both origin and destination station of the route is connected to a metro- or railway- station. The final variation are trips that are not related to the metro/railway system and represents the majority of bikesharing routes in Oslo as presented in Table 3.6. This is explained by a relatively low number of metro/railway stations compared to bikesharing station.

Controlling for urban form at start and end station

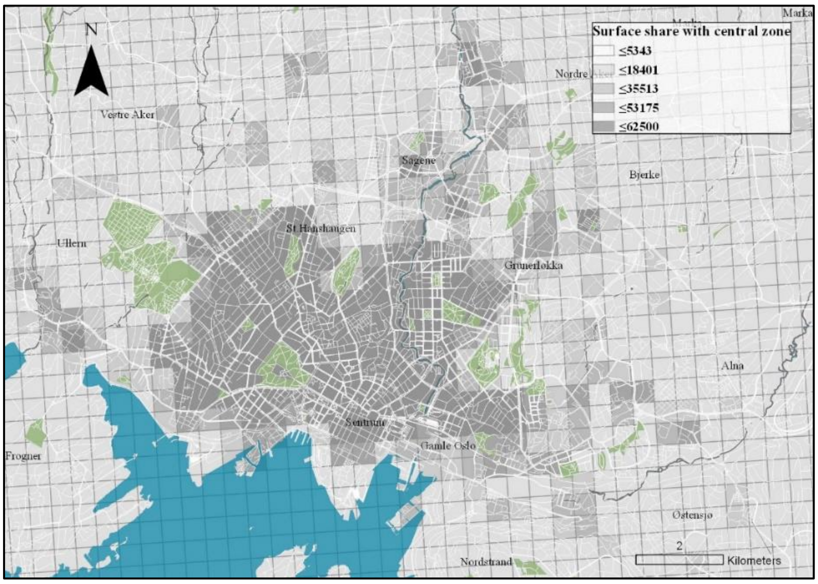
The variables presented in this section are used to measure urban form characteristics at start and end station of a route. The variables will briefly be presented in this section as a more detailed explanation can be found above for Dataset 1.

The variables, *Population density* at start and end station, is the aggregated population within each grid cell of $250m^2$ that falls within the 250m buffers (Statistics Norway, 2016). A Shannon Wiener Index was also here calculated in order to create the variable *building use diversity,* for start and end station of the route. The index is based on residential dwellings, offices, industrial- and educational- buildings, restaurants and hotels in the bikesharing stations' local neighbourhoods.

In this dataset *destination accessibility* is measured differently as any measure of distance to city centre makes little sense as most stations are located in the city centre. The proxy for destination accessibility is therefore a *centrality* variable measuring the share of the area which is in a centre zone. Statistics Norway defines a centre zone as zone that

> "…. consists of one or more centre kernels and a 100-metre zone surrounding them. 2. A centre kernel is an area with more than 3 different main types of economic activity with centre functions. In addition to the retail trade. government administration or health and social services or social and personal services must be present. The distance between enterprises must not be more than 50 metres." (SSB 2017)

The variable thus controls for central areas within the city, as showed in the map in Figure 3.5. The map displays that grid cells with a larger surface share are defined as central zones. The city centre, as well as in the areas Like Ullern, Grünerløkka and Sagene have high centrality values. In the regression analysis the effect of centrality will be measured by an increase of every 1000m within the local neighbourhood of bikesharing stations which is defined to be a central zone.



Figur 3.5: Map demonstrating the surface share of grid cells defined to be a central zone in Oslo.
Source: SSB

Station locks is a variable often included in bikesharing analysis (e.g Tran et.al., 2015; El-Assi et.al., 2017). The number of locks at a bikesharing station essentially informs of its capacity. Centrally located bikesharing stations will in most cases have a higher number of locks and can to certain degrees inform about destination accessibility. As number of locks can impact user frequencies it is important to control for.

<u>Controlling for route characteristics</u>

Distance, a topic briefly touched upon in the introduction to this section, is calculated by conducting a network analysis and used in order to get an indication of how the bikesharers might be cycling between origin and destination station. Open street map is used as a layer, meaning that the GIS takes junctions and edges which represent the actual physical infrastructure in Oslo into consideration when calculating the routes (Esri 2015). Similarly to the OD cost matrix the shortest distance along a network is identified through a GIS.

As argued above it is a weakness that other aspects are not taken into consideration as people will not always chose or have information of low-cost routes even with apps such as Google maps (Hulleberg et. Al., 2018). This is one of the negative aspects of generalisation as it involves loosing detailed information. With that said it is not without a reason that network analysis is based on the assumption of low-cost routes since many people are actively trying to get from origin to destination in the most efficient way. This is especially the case during commuter trips.

The variable *elevation* is created in order to measure the effect hills have on bikesharing route frequencies. As argued in the literature chapter trips that require higher degrees of physiological exertion occur less frequently (Kirkebøen, 2016; Ciari & Becker, 2017). The difference in elevation was therefore calculated by subtracting the elevation of start station from end station. Another weakness of not knowing the exact route is that there might be differences of elevation on the route which might impact ridership levels. The elevations of the stations do however give a good indication of the impact elevation has for route frequency.

Multicollinearity

The correlation matrix in Table 3.5 suggests that there is some correlation between the variables. This is however nearly unavoidable, especially because of the close nature of urban form characteristics (Field 2018; Næss 2012). Field (2018) argues that values above .8 should be omitted and the correlation between building use diversity and employment density is in borderline territory. A VIF test was also conducted and employment density's value exceeded the critical value of >5, further suggesting that the variable could be problematic for the analysis (Field, 2018). It was therefore excluded (Field 2018).

Table 3.5 Pearson's Correlation Matrix

	Population density	Employment density	Building use diversity	Centrality	Route distance	Elevation	Number of locks	Connectivity to metro/railway
Population density	1	-.517**	-.438**	.403**	-.142**	-.068**	-.291**	.154**
Employment density	-.517**	1	.770**	.414**	-.191**	.348**	.125**	-.229**
Building use diversity	-.438**	.770**	1	.329**	-.202**	.396**	.149**	-.169**
Centrality	.403**	.414**	.329**	1	-.361**	.350**	-.195**	-.015**
Route distance	-.142**	-.191**	-.202**	-.361**	1	.000	.076**	-.004
Elevation	-.068**	.348**	.396**	.350**	.000	1	.021**	.007
Number of locks	-.291**	.125**	.149**	-.195**	.076**	.021**	1	.052**
Connectivity to metro/railway	.154**	-.229**	-.169**	-.015**	-.004	.007**	.052**	1

**p<0.01. *p <0.05.

3.4.4 Variable summary table

Table 3.6 presents the descriptive statistics of all variables added in the model.

Table 3.6 Descriptive statistics of variables used to answer RQ2

	Descriptive statistics				Percent pr. category
Variables	**Min.**	**Max.**	**Mean**	**St.Div.**	**%**
Route frequency	0	10218	128.54	325.67	
Morning route frequency	0	2249	13	43.12	
Afternoon route frequencies	0	1431	20	47.09	
Connectivity to Metro & railway <200m					
Metro/rail connectivity at destination					9.7
Metro/rail connectivity at origin					9.7
Metro/rail connectivity at origin and destination					1.1
No connectivity to metro/rail					79.5
Station characteristics					
Population density	0	1513	650	440	
Land use mix	.182	1.67	.877	.345	
Station locks	6	60	22.6	9.71	
Route characteristics					
Distance	0	9736	2708.89	1461.47	
Elevation	-130.33	130.33	0	43.07	

3.5 MODELS

3.5.1 Generalised linear models

The models used in the thesis are all generalised linear models (GLM). GLMs are a family of a broad class of statistical models which allows the dependent variable not to have normal distribution (Agresti 2007). GLMs are therefore often used for count data expressed as proportions (ordinal logit regression) for binary response outcomes (Binary logit regression) and for non-proportional count data (log-linear models. i.e negative binomial regression). These models rest on some common assumptions. Firstly, the observations are independent of each other, meaning that the cases in the sample are not influenced or related to other cases.

Secondly, that there is a linear relationship between any continuous independent variable and the logit of the dependent variable. Finally, the maximum-likelihood estimation used in GLMs is reliant on sufficiently large samples.

The only assumption that potentially is violated in this case is the first assumption regarding independence of cases for bikesharing mobility analysis. As stated in Tobler's first law of geography "…near things are more related than distant things" (Tobler 1970, In Miller, 2004 p.284). This could essentially mean that bikesharing stations in close proximity to each other are spatially auto-correlated (Noland et.al., 2016). This means that stations that are close to each other may be more alike and thus not independent of each other. A Moran's I test can be used to test autocorrelation and is pretty straight forward for OLS models. A Moran's I test embedded in GLM models, on the other hand, requires complex methods that go beyond the scope of this thesis. The results from Noland et.al.'s (2016) study where spatial-autocorrelation was tested for, suggested that this is not a common problem. Special concern is however taken in the interpretation of analysis involving bikesharing stations.

Common goodness-of-fit measures for generalized linear models are the Pearson and deviance statistics, which are weighted sums of residuals (Cameron & Trivedi, 1998). These form the basis of the pseudo R^2 statistic which is often used analogues to the R^2 statistics in OLS regressions. The pseudo R^2 statistic varies from 0 to 1, where values close to zero indicate that the model contributes little in explaining the variation in the dependent variable, and values close to 1 explain much of the variation in the dependent variable (Field, 2018). The pseudo R^2 statistic is however by no means an accurate measure and should not be interpreted the same way as the R^2 in linear models.

The Wald-statistic also known as the Z-statistic is a significance test used for hypothesis testing. The Wald statistic is used in all the models in the thesis and tells whether the coefficients are significantly different from zero (Field, 2018). If this is the case it can be assumed that the independent variables are making a significant contribution to the prediction of the outcome and the null hypothesis can be rejected.

3.5.1.1 Ordinal logit

An ordinal logit model is applied to address RQ1 by estimating the effect of daily mobility patterns and transportation resources on interest in bikesharing participation whilst controlling for individual characteristics, attitudes and urban form. Logit models are well suited for categorical dependent variables where the aim is to predict which category an entity falls within (Field 2018). The dependent variable for this model is stated interest in participating in bikesharing with values varying from 1-7, where 1 is not interested and 7 is very interested. The values are ranked, but the distance between the categories remain unknown (Norusis 2009). Ordinal variables are sometimes treated as continuous variables and other model fits, like multinomial logit regressions are often used. An ordinal logit model was however chosen because it incorporates the ordinal nature of the dependent variable.

Logistic regression estimates the probability of an event occurring. The calculation is based on the ratio of people who experience the event to the number of people who do not. The odds of being very interested is for example the ratio of the number of people who scored 7 to the number of people who gave other scores. The model coefficients, often referred to as logits, estimate the log of the odds that an event occurs. The coefficients thus tell how much the logit changes based on the values of the independent variables (Norusis, 2009). Positive values indicate that the probability of having higher values on the dependent variable increases, whereas negative values indicate that there is a higher likelihood of being less interested in bikesharing membership.

Ordinal logit models are often referred to as proportional odds models because the model builds on an assumption that the relationship between the independent variables and the logits are the same for all the coefficients. This means that the results are a set of parallel lines one for each category of the dependent variable (Norusis, 2009). Violating the assumption can result in incorrect model interpretation (Ari & Yildiz, 2014). The assumption of parallel lines is tested in SPSS and if the lines are parallel the respective significance level should be large.

3.5.1.2 Binary logit

A binary logit model is used to measure the effect of daily mobility patterns and transportation resources on revealed membership choice whilst controlling for individual characteristics, attitudes and urban form. The results from the regression model will be used for comparison with the ordinal logit model in order to answer RQ1. Binary logit models are used when the categorical outcome variable is binary, which is the case when it comes to revealed bikesharing membership choice (Field, 2018). Respondents who fall under value 0 have no membership, whereas respondents who have a membership fall under value 1. It is therefore not possible to have the score 0.5 as it is not possible to fall somewhere between having a membership or not having a membership.

Like ordinal logit regression binary logit regression estimates the odds of a certain event occurring (Field, 2018). In this case it is the event of having a bikesharing membership. In the binary logit model the odds of having a bikesharing membership is the probability of getting 1 divided by the probability of getting 0. The logistic regression calculates changes in the log odds of the dependent and not the changes in the dependent variable in itself as in OLS regressions (Garson, 2016). The coefficients demonstrate what the probability is for having a bikesharing membership. 0 means that the independent variable does not increase or decrease the probability of having a bikesharing membership, whereas positive values indicate a higher probability and negative values indicate a decreased probability of having a bikesharing membership. The respective Wald statistic tells whether the independent variable is significantly different from zero.

3.5.1.3 Negative binomial regression (NBR)

A negative binomial model was applied to estimate the effect of public transportation connectivity on bikesharing route frequencies whilst controlling for urban form and route characteristics. This model was chosen mainly because the dependent variables are based on count data requiring special types of regressions (Cameron & Trivedi, 1998). Poisson regression and negative binomial regression are generalised linear models fitted for such data (Hilbe, 2012). Negative binomial regression (NBR) come in many forms and is a generalisation of a Poisson regressions as it is based on Poisson-gamma-matrix distribution. The main difference is that the NBRs have fewer restrictive assumptions and often are used when the count data is over-dispersed. Overdispersion occurs when the conditional variance exceeds the conditional mean (Cameron & Trivedi 1998). Using a Poisson model with over-dispersed data can result in underestimating the variance of the coefficients producing misleading conclusions (Lee et.al, 2012). The histogram in Figure 3.6 shows that *route frequency* has a Poisson distribution, in addition to showing clear signs of overdispersion as the standard deviation by far exceeds the mean route frequency[4]. A negative binomial regression was therefore chosen as it is more robust towards overdispersion. The NBR is a log-linear model and the parameter estimates indicate the expected increase or decrease in expected log count. One unit increase in one of the independent variables thus demonstrate the change in expected log count of bikesharing routes (Cameron & Trivedi 1998). Put differently positive coefficient values are linked to higher route counts whereas negative coefficient values indicate lower route frequencies.

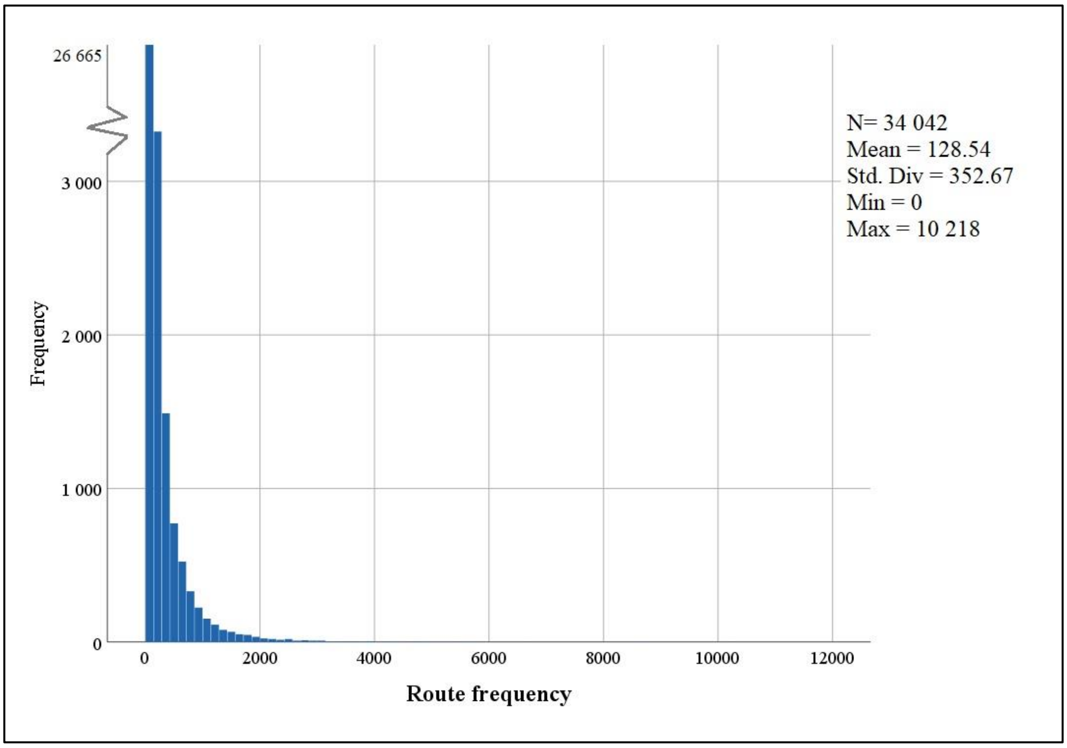


Figure 3.6: Histogram of route frequencies illustrating the poisson distribution of the dependent variable.

Negative binomial regressions are sensitive to small samples and high amounts of zero values (UC, 2019). The distribution in the variable shows a high amount of zeroes, and a zero inflated negative binomial regression (ZINB) deal better with high zero counts. However, of theoretical consideration the NBR model was favoured, and the choice landed on this model after running a ZINB model where coefficient values and significance levels were highly similar[5].

[4] The variables *morning route frequency* and *afternoon route frequency* also have a Poisson distribution with signs of overdispersion.

[5] ZINB models have two output models, one full model which is similar to the NBR output and one inflated model which predicts zero outcomes, i.e why some routes always have zero frequencies (Lee et.al 2012).

3.6 CONCEPTUAL MODEL

The model in Figure 3.7 presents how the RQs regarding bikesharing integration with public transportation will be answered. Dataset 1, with individuals as cases, is suited for the question regarding bikesharing integration in daily mobility. Logit models will be used in order to test the effect of transportation resources and daily mobility pattern on stated interest in bikesharing participation and revealed membership choice. Control variables related to urban form at residency, individual characteristics and attitudes are added to isolate the effect.

Dataset 2, with bikesharing routes as cases, is used to address RQ2 whether bikesharing is integrated with the metro/railway system on individual trips. The test variable Metro/railway connectivity is used to see whether bikesharing is used for access and/or egress trips. Controlling for urban form and route characteristics is important as many factors can generate high route frequencies. The results from these analyses will be presented in the next two chapters.

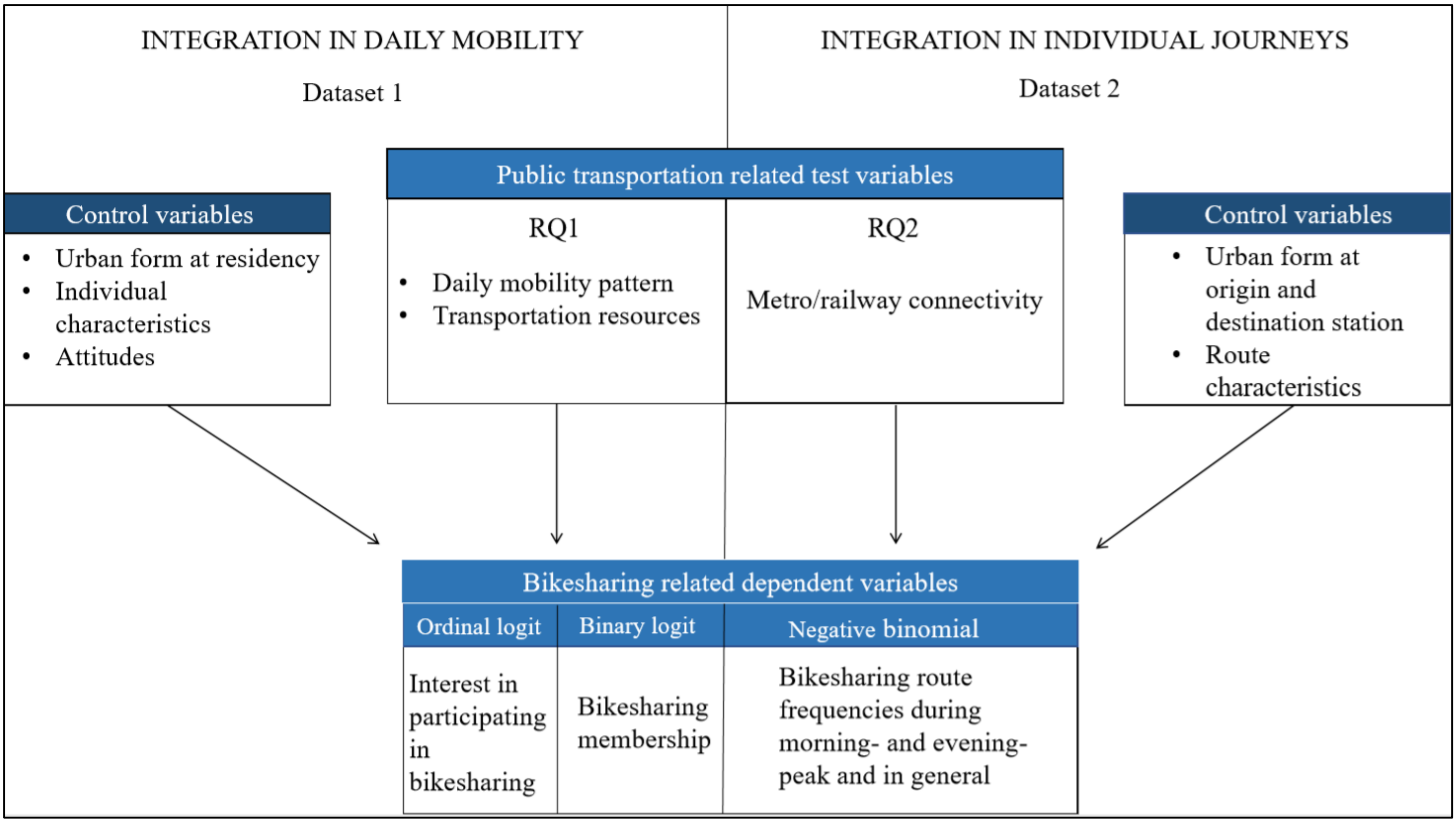


Figure 3.7: A conceptual model summarizing how RQ1 and RQ2 will be addressed in the thesis.

4 RESULTS PART I

Integrating bikesharing in daily mobility

The aim of this chapter is to see in what way access and use of certain mobility forms may be linked to increased likelihood of having a bikesharing membership compared to just being interested in bikesharing participation. This will be done by addressing RQ1:

How do daily- access and use of public transportation affect revealed bikesharing membership choice compared to stated interest in bikesharing participation?

In this chapter will the relationship between daily- access and use of public transportation modes and stating interest in bikesharing participation be explored. The same independent variables will be used in order to see which factors are affecting revealed membership choice, forming a basis for comparison. By comparing results, it is possible to identify factors that might be decisive for bikesharing integration in daily mobility. This kind of method I view to be more beneficial than just comparing members from non-members as not all non-members would even consider bikesharing.

The literature review in chapter 2 forms the basis of the hypothesis in this chapter, which is that bikesharing is expected to be more relevant for people who are reliant on a broader mix of transportation resources in their daily mobility pattern (Bachand-Marleau & El-Geneidy, 2012). This might especially be the case for people who already have a habit of intermodal travel (Morris & Khan, 2009). I expect that bikesharing is less relevant for people with access to cars who already can cover door-to-door transportation and might therefore not be reliant on a broad mix of transportation modes. As much research has pointed to a relationship between bike ownership and bikesharing, I expect similar results from the regression models (Adams et.al. 2017, Fishman et.al., 2013). Furthermore I expect that the urban form in the respondents' local neighbourhood will have an effect on bikesharing interest and membership (Liu et.al., 2012).

A time geographic framework will be used to understand results from this chapter. Individuals' space-time prisms are related to different constraints that can impact which transportation modes are relevant for them (Miller, 1991). Spatio-temporal opportunities and constraints related to residential area, transportation resources and daily mobility pattern might not only impact how people are travelling, but also the types of transportation modes that are of interest. A time geographic approach may therefore further help understand how access and daily use of transportation modes are related to membership choice compared to interest in bikesharing participation.

I will start by exploring the relationships, descriptively viewing the individual relationship between the variables with stated interest in bikesharing participation and revealed membership choice. Thereafter the results from the ordinal logit model and binary logit model will be presented. Individual characteristics and attitudes are controlled for in order to see the effect of transportation resources and daily mobility pattern on stated interest in bikesharing participation and revealed membership choice.

4.1 DESCRIPTIVE RESULTS

Recalling the methods chapter, the two dependent variables used to answer RQ1 measure two quite different aspects of bikesharing. The first variable is ordinal, measuring the respondents' stated interest in participating in bikesharing. The second dependent variable is binary, measuring actually revealed bikesharing membership in the sample. These two variables will briefly be presented again as this section is dedicated to the descriptive relationship between the independent variables on the dependent. By exploring the descriptive relationships, questions can be raised about what to expect from the regression models.

4.1.1 The dependent variables – Bikesharing interest and bikesharing membership

The graph in Figure 4.1 presents the different levels of stated interest in bikesharing participation. Nearly half of the sample state to be interested, but the majority show lower levels of interest[6]. The question therefore is, what impacts peoples' interest in shared mobility services like bikesharing?

[6] Values 5-7 on the dependent variable indicates high levels of interest in bikesharing membership whereas values 1-3 indicate low levels of interest.

In chapter 3 the question was raised whether the variable actually is measuring intention of participating or if it is more a positive perception towards bikesharing in general. The high amount of respondents who show interest compared to actual membership amongst the respondents can suggest that the variable is more a reflection of opinion than intention.

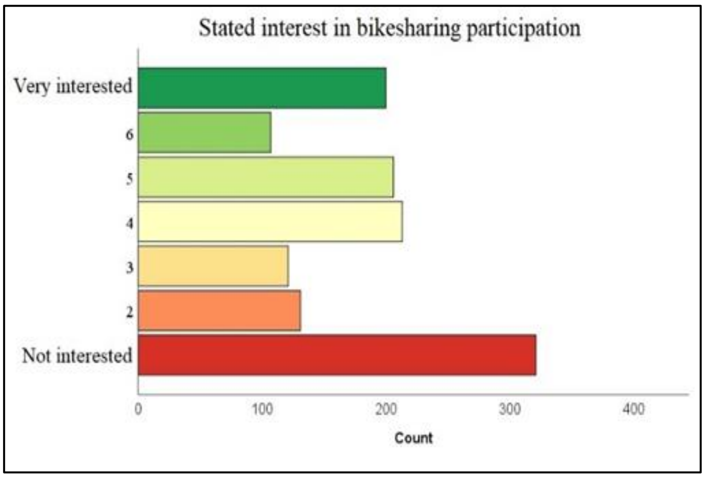


Figure 4.1: Graph of stated interest in bikesharing participation

The second dependent variable is more tangible as it measures an actual outcome; either you have a membership, or you do not. By discovering whether mobility related to public transportation increases the likelihood for actual membership choice it can inform about public transportation integration with bikesharing in daily mobility.

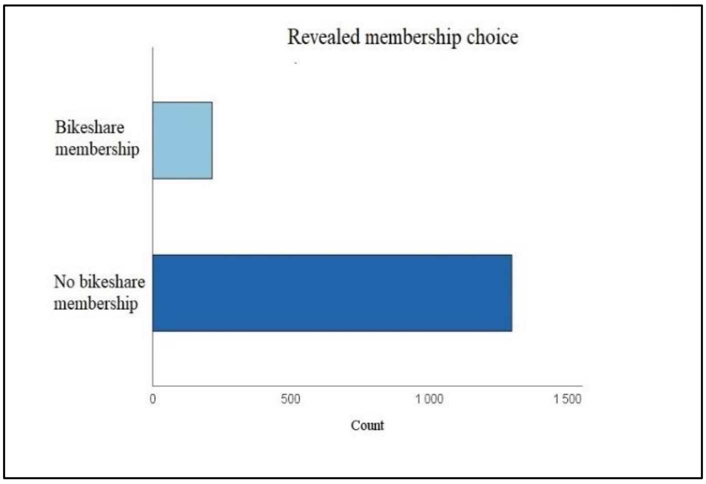


Figure 4.2: Graph of revealed membership choice

4.1.2 Transportation resources

Does the ownership (or lack of ownership) of certain transportation resources make bikesharing a more attractive transportation mode? In line with the hypothesis, the graphs in Figure 4.3 show that the part of the sample without access to a car are more positive towards bikesharing participation compared to those with car access. As pointed out in the literature review, people without car access often live in denser areas and are more dependent on their direct residential area, thus having shorter travel distances (Williams et.al, 2003). Bikesharing, a transportation mode linked to shorter travel distances may therefore be more interesting for people without car access (Castillo-Manzano et.al., 2016). Furthermore, the respondents with access to cars have an extensive spatial reach, compared to the respondents who do not have access to a car. Bikesharing might therefore be more relevant in situations where it can contribute to lifting spatio-temporal constraints. Nearly 80 % of the samples' bikesharing members do not have access to a car indicating that there might be a relationship between not having access to a car and bikesharing membership. With that said a surprisingly large amount of the sample with car access state interest in a bikesharing membership. Contradicting the hypothesis

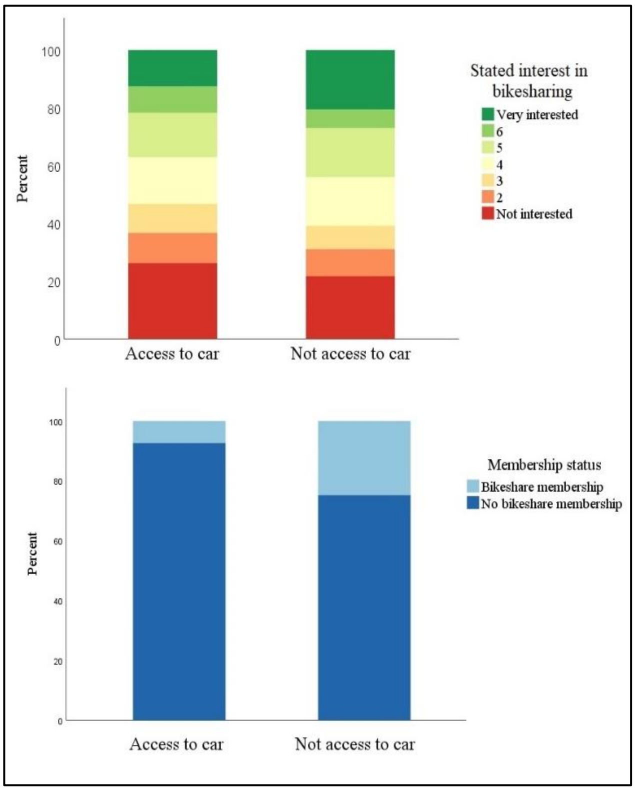


Figure 4.3: Graph presenting descriptive relationship between access to car and interest in bikesharing and revealed membership choice

Figure 4.4 tells that all the bikesharing members in the sample do for instance also own their own bike. Respondents with an own bike also report higher levels of interest in bikesharing participation. The descriptive relationships are very much in line with what earlier research has found on the topic (Fishman et.al 2013). The result is however somewhat counterintuitive from a time geographic perspective, as respondents are not adding a new mobility mode to their daily mobility mix. With that said the result can point to bikesharing being used in situations where their private bike is not accessible, subsequently changing individuals' space-time prisms.

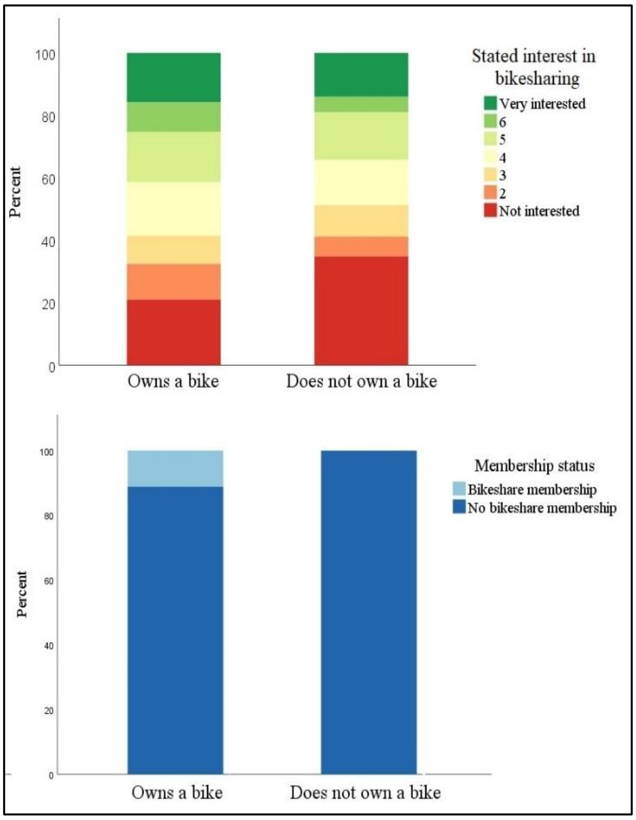


Figure 4.4: Graph presenting descriptive relationship between bike ownership and interest in membership and revealed membership choice

Both previous literature on the topic and the Pearson's correlation matrix presented in chapter 3 indicate that transportation resources are related to each other, and viewing them separately can be somewhat tricky (Næss, 2016; Cervero & Kockelman, 1997). These variables will therefore be presented and viewed together in the regression models. In this section, however, only the descriptive relationship between the dependent variables and the urban form characteristic *distance to public transportation* will be presented. This relationship is presented because of its relevance in light of the research question, highlighting the importance between public transportation and bikesharing.

Seeing if there is a relationship between proximity to public transportation and stated interest as well as membership may indicate whether bikesharing has an integrational potential with public transportation, especially if bikesharing is being used for access and egress trips (Bachand-Marleau & El-Geneidy, 2012). The graph in Figure 4.5 however does not suggest any obvious association between stating interest and living close to public transit[7]. Bikesharing members in the sample, on the other hand, generally live closer to public transportation than non-members. If this is meaningful for bikesharing membership or if it is just a result of urban living conditions will become clear after running the regressions, where the other urban form characteristics are controlled for.

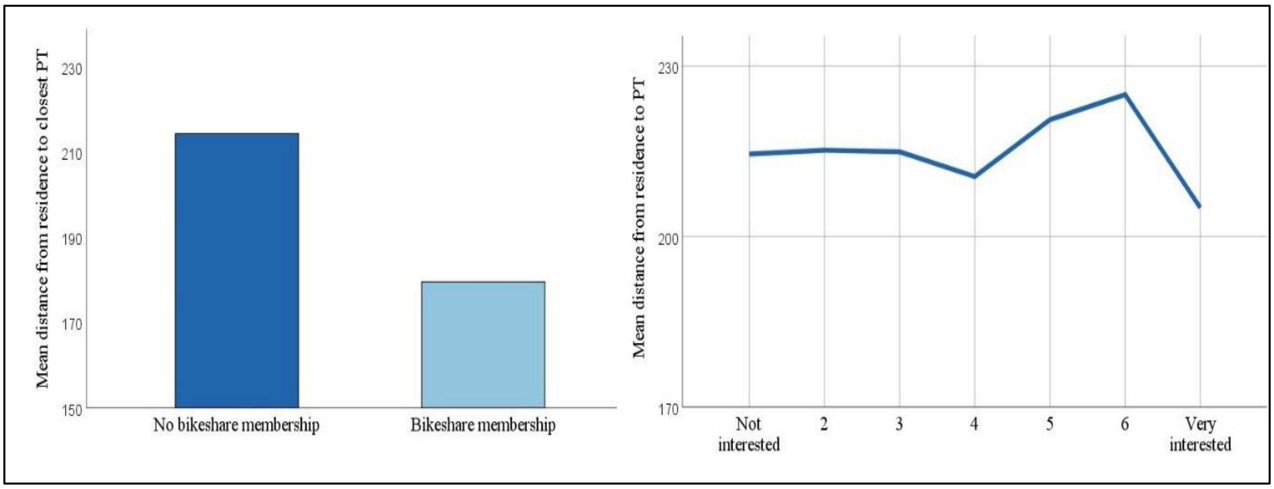


Figure 4.5: Graph and line chart illustrating distance to public transportation from respondents' residences in relation to the dependent variables

[7] For illustrative reasons the normal distance to public transportation was used in the graph. In the regressions the logarithmic distance will be used instead as this measure was proven to be more fitting for the models.

4.1.3 Daily mobility patterns

The research presented in the literature review indicated that an intermodal mobility pattern might be linked with bikesharing. Do the descriptive results suggest the same relationship in Oslo and Bærum?

The first graph presented in Figure 4.6 illustrates a general pattern: Stated interest in participating in bikesharing increases with the frequency of public transportation trips during a week. The bikesharing members in the sample on the other hand seem to be moderate public transportation users, as around 60% of bikesharing members reported to have used public transportation between 1-10 times the past week.

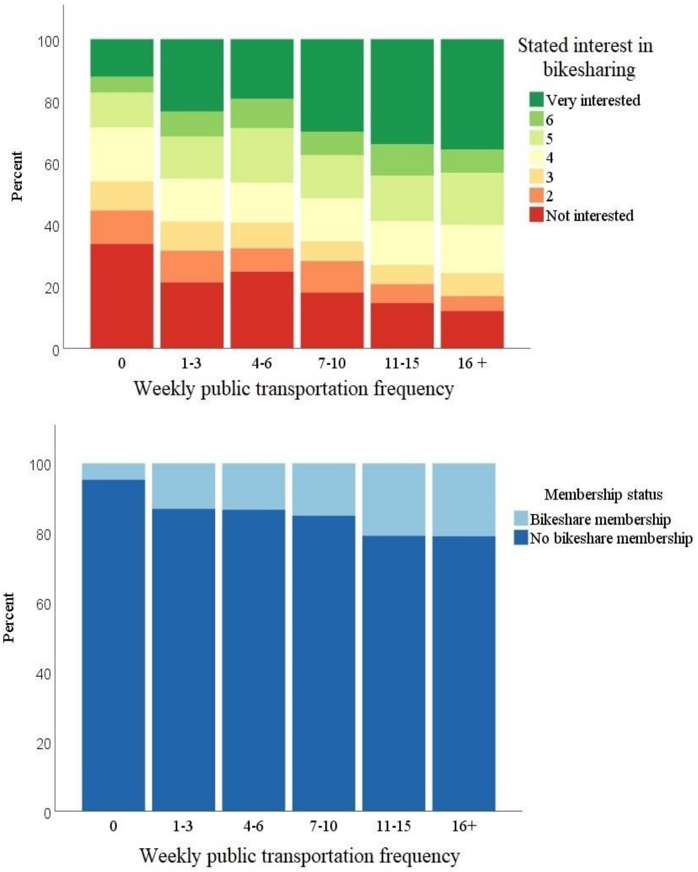


Figure 4.6: Descriptive relationship between public transportation frequency and interest in bikesharing as well as revealed membership choice

Because stated interest is higher for frequent public transportation users, and bikesharing members in the sample use public transportation less frequently, it can, in light of the integration vs substitution debate presented in the literature review, suggest that bikesharing members are substituting public transportation trips with bikesharing (Fishman et.al, 2013). Commenting this with any certainty would however require a different type of data and method, for example a longitudinal study with fixed effects (Gordon, 2016).

The graphs in Figure 4.7 illustrates respondents' different daily mobility mix and how this is related to interest levels as well as membership. The four different combinations are 1) respondents who stated to only have travelled by public transportation during the past week, 2) respondents who travelled by both bike and public transportation the past week, 3) respondents who only stated to have travelled by bike the past week and finally 4) the group who travelled with other transportation modes most likely driving or walking. The respondents who only reported to have travelled by public transportation show greater interest towards bikesharing participation than the respondents who only reported to have cycled the past week. In light of earlier research this is interesting because bike ownership has proven to be an important explanatory variable for bikesharing membership (Adams et.al., 2017). Furthermore, only 2 percent of the sample's bikesharing members state to only have cycled the past week. This can indicate that bike ownership on its own cannot adequately explain bikesharing membership. How the privately-owned bike is used may be equally important for membership choice as a bikesharing bike is often used for intermediary distances and has other trip purposes compared to a privately owned bike (Martens, 2006; Castillo-Manzano et.al., 2016).

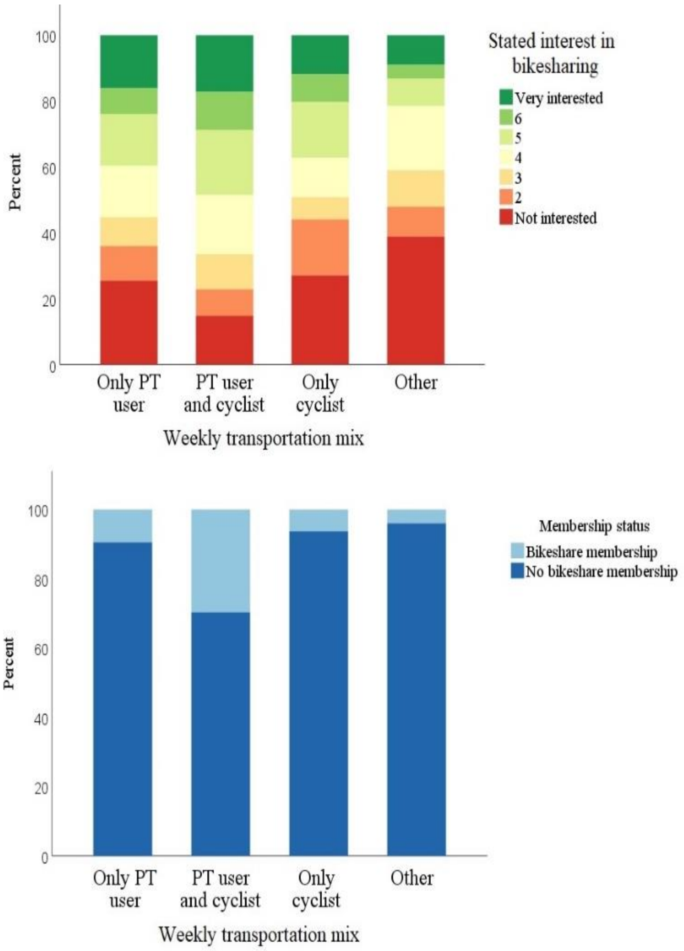


Figure 4.7: Descriptive relationship between daily mobility mix and interest in bikesharing as well as revealed membership choice

This argument is supported by the fact that it is the daily mobility group that combines cycling and public transportation who report to be most interested in membership. This is also the mobility pattern which is by far the most common for the sample's bikesharing members, suggesting integration between public transportation and bikesharing in daily mobility. The category *other*, of which the majority most likely drove or walked, is the group which is the least interested in bikesharing participation. Just under 3% of the sample who has a bikesharing membership fall under this category.

The descriptive results presented this far indicate that transportation resources and daily mobility patterns related to public transportation might be affecting stated bikesharing interest as well as actual membership. However, such relationships are never simple and other factors like individual characteristics, attitudes and urban form will most likely also impact interest in shared mobility services such as bikesharing. These relationships will briefly be presented before continuing to the results from the logistic regressions.

4.1.4 Individual characteristics

Some common characteristics for bikesharers was presented in the literature review; they tend to be highly educated, having an above average income and are disproportionately males in their early 30s (Shaheen et.al., 2012; Fishman et.al., 2015, Guo et.al., 2017). Since resources, preferences and constraints are not context free and are related to people's socio-demographics it is important to explore how individual characteristics are related to stated interest and revealed membership choice (Dijst, 2013). Different individual characteristics may therefore help explain differences between the respondents who state to be interested in bikesharing participation and the respondents who already are members?

Table 4.1 suggests that membership and age have a negative association. The majority of members are between 18-35 years old. Stating interest in bikesharing participation is also negatively associated with age. Furthermore Table 4.1 shows that mean interest among females is somewhat larger than male's interest in bikesharing membership. There are more female bikesharing members in the sample than males contradicting results from other cities. This may of course only be by chance and it will first become clear in the regression models if there is a significant difference between males and females in Oslo and Bærum (Rubin, 1985). A noteworthy weakness with the membership measure is that we do not know if these members are frequent users of the bikesharing program or not, an aspect that previous studies have seen manifestations of gender differences (Adams et.al, 2017).

Variables	Interest in bikesharing	Membership status in percent	
Individual characteristics	Mean interest	No membership	Membership
Age: 18-35	4.21	37.12 %	11.03%
Age: 36-55	3.65	33.42%	2.51%
Age: 56+	2.85	15.26%	0.66%
Male	3.64	42.67%	6.87%
Female	3.86	43.13%	7.33%
Lower Education	3.53	23.25%	3.10%
Higher education	3.83	62.55%	11.10%
Income <1000 000	3.78	61.31%	11.53%
Income >1000 000	3.69	24.21%	2.95%

Table 4.1: Individual characteristics and interest levels as well as percentage of members and non-members in each category

As for education the group with a university degree or equivalent state to be more interested than the group without higher education, being in line with findings presented in the literature review (Fishman et.al., 2013). Interestingly the share of the sample with a household income above one million NOK is more negative towards bikesharing membership. Following results from earlier research it should be the other way around (Shaheen et.al., 2011). The majority of the bikesharing members also fall in the "lower income" category. The result is however not surprising as the majority of the bikesharers in the sample are in their late 20s, many of whom probably live in single income households.

The descriptive results show similarities between the individual characteristics of those who state to be interested in bikesharing membership and those who have taken a membership choice. Firstly, age is negatively associated with stating interest as well as having a membership. Secondly, females show a higher degree of interest in membership, as well as the percentage of female bikesharing members being slightly higher. Thirdly, higher education is also linked to higher interest in the sample, as well as membership by far being more prominent in the group with university education. Finally, the sample results suggest a negative relationship between household income and membership as well as for stated interest in participation.

The descriptive results may be understood as a consequence of different time geographic constraints, preferences and resources related to individual characteristics. The low percentage of bikesharing members and lower interest rates related to age might for example be a manifestation of the respondents' possibility boundaries; the paths available for individuals and groups to fulfil their projects (Gregory et.al., 1994). Age may not only be related to physiological constraints, but also to education, income and subsequently different resources. The individuals' characteristics can therefore be related to having access to- and using- different transportation modes which are more fitting for their space-time prisms.

4.1.5 Attitudes

Attitudes effect personal transportation decisions (Morris & Khan 2009). Especially environmental consciousness has had a significant impact on daily travel behaviour (Prillwitz & Barr, 2011). Only looking at socio-demographic variables to control for transportation resources and daily mobility patterns will therefore not hold. The graphs in Figure 4.8 illustrates the difference in attitudes between the respondents with bikesharing membership and the respondents without membership.

Transportation choice is to a certain degree linked to price and economic orientation as argued in chapter 2, and may therefore impact daily mobility choices (Gardner, 2009; Riggs, 2017). Since bikesharing is a relatively cheap transportation mode in Oslo this can impact membership choice in addition to affect stated interest in participation in bikesharing (Obos, 2017). The majority of the sample state to be economically oriented and there is no obvious difference between members and non-members. Similarly are there no obvious differences between members and non-members in environmental consciousness illustrated in Figure 4.8b. The part of the sample with bikesharing membership do however show a slight tendency to be more environmentally conscious, supporting the hypothesis that green values affect travel behaviour. With that said the weight of the whole sample is towards the environmentally friendly end of the scale. Interestingly, Figure 4.8b on stated interest, suggest that environmental consciousness might be related to being interested in bikesharing.

Bikesharing has become a visible transportation mode in many cities, so much so that it has been suggested that bikesharing is becoming part of an urban identity (Langfeldt, 2011). It was therefore argued in the theory chapter that bikesharing may be associated to having an urban outlook. The graph presented in Figure 4.8C illustrates that a higher percentage of bikesharing members prefer to live in urban areas rather than in rural areas. The answers can however be influenced by urban living conditions, which will be controlled for in the regressions.

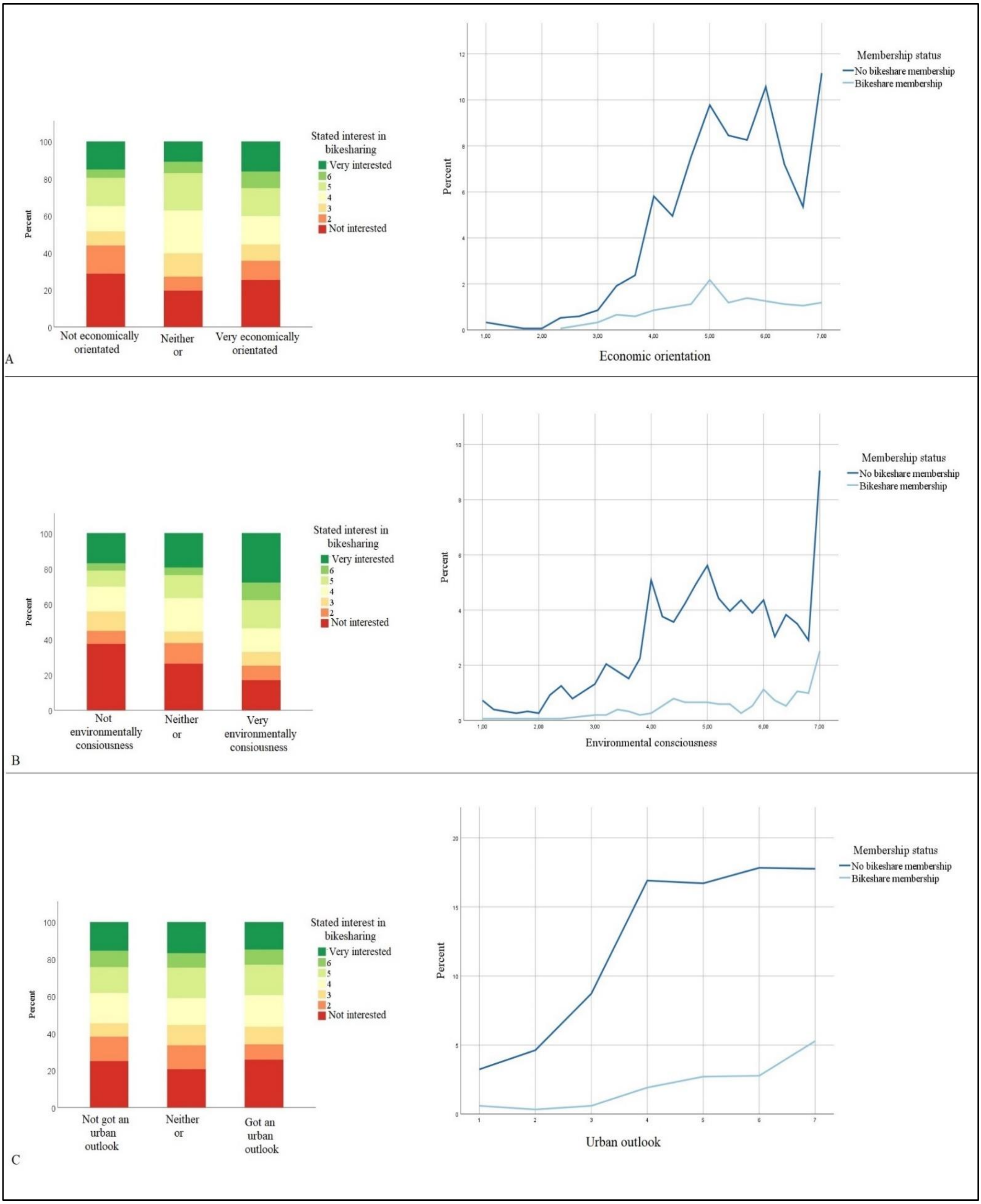


Figure 4.8: Descriptive relationship between economic-, environmental- and urban- attitudes on stated interest and revealed membership choice illustrated in bar- and line- charts.

4.1.6 Summing up the descriptive relationships

The descriptive relationships suggests that there are many similar factors that may be associated with stating interest and being a member. Transportation resources, like not having access to a car and owning a bike, seem to be related to stated interest in participating in bikesharing as well as actually revealed membership choice. Furthermore, the results indicate a relationship between daily mobility patterns linked to public transportation and stated interest and revealed membership choice. However, from the descriptive statistics distance to public transportation only indicated a relationship between bikesharing membership and not stating interest.

The descriptive statistics presented above do however show a highly simplified picture of the relationships that can be expected to be found. Urban form, individual characteristics and attitudes can to varying degrees interplay and affect the dependent variables. In order to say anything substantial about bikesharing integration with public transportation these factors need to be controlled for in a regression.

4.2 ACCESS AND USE OF PUBLIC TRANSPORTATION AND HOW THIS AFFECTS STATED INTEREST IN PARTICIPATING IN BIKESHARING

4.2.1 Model interpretation

An ordinal logit model was used to demonstrate the effect of transportation resources and daily mobility patterns on stated interest in participating in bikesharing. A stepwise model build-up is used to demonstrate the relative effect of the added variables. The first step in the models only include individual characteristic variables. In the second step attitude variables are added, followed by urban form and transportation variables in the third step. In the final step the daily mobility pattern variables are included. Parsimony is an ideal for the statistical model build-up and variables that neither are of theoretical importance nor substantially benefitted the model is excluded (Field, 2018). In logistic regression simpler models are also preferred because the models require an adequate count in each cell. The presence of empty or small cells can cause instability in the models and give unnaturally high coefficients (Garson, 2016).

In logistic regression pseudo R^2 is used to measure the independent variables' overall explanation of the variation in the dependent variable (Norusis, 2009). The pseudo R^2 statistics are not straight forward in their interpretation and should be used with some caution. The statistic is however helpful in understanding the relative explanatory power for the different models. In the models in Tables 9 and 10 Nagelkerke's R^2 will be presented. The statistic varies from 0 to 1 and indicate whether the inclusion of new variables improve the model's overall explanatory power (Field 2018).

Even though the basic interpretation of a binary- and an ordinal- logit model is fairly similar the interpretation of the coefficients is different. The coefficients demonstrate the change in the natural log of the odds of the dependent variable for one unit increase in the independent variable (Garson, 2016). Coefficient values above zero indicate a heightened likelihood for stating a higher level of interest, whereas negative values are associated with a likelihood of a lower interest score (Norusis, 2009). Coefficients for categorical independent variables tell if the likelihood is higher or lower for being interested in participating in bikesharing than the reference category, which is held at zero.

The z-scores, which are presented in brackets in table 4.2 are chi-square tests and signify whether the coefficients' values are significantly different from zero (Field, 2018). If this is the case, can it be assumed that the independent variable is making a significant contribution to the prediction of stated interest in participating in bikesharing. The significance levels of 90, 95 and 99 percent are used. Extra caution is taken when interpreting variables with a 90 percent significance level, as low significance level increases the chance of rejecting a true null hypothesis (Gordon, 2016).

4.2.2 Step I- The effect of individual characteristics

The first step of the model build-up only includes individual characteristic variables. Age has a significant negative effect on stating interest in bikesharing participation, a result in line with previous literature (Efthymiou et.al 2013; Fishman et.al., 2013). A one unit increase in age is associated with a -.031 log odds of being in a lower interest category. It is not surprising that the likelihood of wanting to join a bikesharing programme decreases with age. This relationship may best be explained by the capability and coupling constraint presented in time geographic theory. Not only is age related to limited physiological capacity, but also with different coupling constraints in form of mandatory activities at multiple locations (Miller, 1991). Age may therefore be related to time space prisms where bikesharing cannot adequately expand the individuals' spatial reach.

As suggested by the descriptive statistics, having a university degree or equivalent is significantly associated with a higher probability of stating interest in participating in bikesharing on a 5 percent significance level. Gender, a variable that in previous studies have proven to affect bikesharing, is however not significantly related to stating interest in participation (Liu et.al., 2012; Adams et.al., 2017). Furthermore, there is no significant difference between the income categories, another variable which in previous studies have impacted interest in bikesharing participation (Efthymiou et.al 2013). A regression with three- and six-income categories has also been run in all models, without showing any significant effect. This could as mentioned above be a result of the measurement being household income and not individual income.

4.2.3 Step II - The effect of attitudes

Adding variables measuring the effect of attitudes improves the model, demonstrated by the increase of the pseudo R^2 value from .064 to .093. The coefficients illustrate that most of the explanatory power lies in being environmentally conscious. As argued in the literature review, green values and beliefs impact people's transportation choices (Kahn & Moris, 2008; Prillwitz & Barr, 2011). This also seems to be reflected in stated interest in participating in bikesharing. Relatively high coefficient values indicate that environmental consciousness can be strongly associated with stating interest in participation, supported by high z-scores. The significant association between environmental consciousness and a higher interest level may also indicate that bikesharing is perceived to be a sustainable transportation mode.

This variable may also have impacted the decrease in strength of education, as education and environmental consciousness is known to be related (Hampel et.al, 1996). The two other variables; economic orientation and urban outlook are however not significant. These results are interesting in itself because bikesharing is an affordable transportation mode (Efthymiou et.al 2013). Bikesharing should therefore be an attractive transportation mode for economically oriented people. Furthermore, earlier research has emphasised the role price plays for bikesharing membership (Fishman et.al 2013). The result could of course be related to lack of knowledge as non-members may not be aware of the price tag of membership.

4.2.4 Step III - Effect of urban form and transportation resources

In the third step variables related to urban form are added measuring; density, diversity, destination accessibility and distance to transit in addition to the transportation resource variables; access to car and bike ownership. The Pseudo R^2 increases from .093 to .106 improving the overall model. The change in R^2 was however higher from the first step to the second step indicating that attitudes are more important in explaining the variation in the dependent variable.

Recalling the literature review, urban form is important in explaining bikesharing behaviour (Campbell & Brakewood, 2017; Liu et.al., 2012). Urban form is however not a variable typically used for measuring interest in mobility, explaining why urban form is not significantly affecting stated interest in bikesharing participation. This result therefore suggests that urban form is less important for explaining abstract things, such as interest levels in transportation modes.

Transportation resources only seem to have a marginal effect on interest in participation. As suggested by the descriptive statistics, the logarithmic distance to public transportation, the urban form variable saying the most about access to public transportation, has for instance no effect on the dependent variable. Neither does having access to a car. Bike ownership on the other hand has a relatively strong and significant effect on stating interest in participation. This result is in line with the hypothesis presented in the introduction of the chapter as well as key findings presented in the literature review (Fishman et.al, 2013; Adams et.al., 2017).

The results from this step is somewhat paradoxical as the only transportation resource which increases the likelihood of being interested in participating in bikesharing is also a transportation mode the respondents already have access to. This result suggests two things; firstly, that bikesharing is highly reliant on skills which come with owning a bike. Secondly, that a bikesharing bike may have a potential to fill a need which the privately-owned bike cannot adequately fulfil, like for example one-way trips and access/egress trips. For such trips bikesharing might have the potential to change the space-time prism of individuals by lifting time geographic constraint relative to walking. Bikesharing may therefore have a potential to be supplementing other sustainable transportation modes rather than substituting them.

The non-existing relationship between distance to public transportation and interest in participation illustrates that bikesharing does not show an immediate potential to either being integrated with or replacing public transportation. This may however change when the daily mobility pattern variables are added in the fourth step.

4.2.5 Step IV - Effect of daily mobility patterns

By adding the new variables in the final step, the R^2 value increases from .106 to .119. Daily mobility patterns that are related to frequently using public transportation is statistically significant on a 95 percent level. The coefficient demonstrates that a one unit increase in public transportation frequency is associated with .081 change in log odds for having a higher interest level. Combining cycling and public transportation is also a mobility pattern that is associated with being more positive toward participating in bikesharing, a finding similar to previous studies (Bachand-Marleau & El-Geneidy, 2012).

The results related to daily mobility patterns are very much in line with the results presented in the descriptive statistics section. People who have a mobility pattern dominated by cycling are not significantly different from drivers and pedestrians in stating interest in bikesharing participation. An indication that there is a distinction between owning a bike and using it regularly (Castillo-Manzano et.al., 2016). The same results are found for people who mainly use public transportation, however the frequency of trips matter.

The daily mobility pattern where cycling and public transportation is combined is significantly different from the reference group. The result is in line with the hypothesis: People who already have a habit of combining the transportation modes are more positive towards the idea of participating in bikesharing. The coefficient estimate is relatively high compared to public transportation frequency and bike ownership. The result is also consistent with Lanzini and Khan's (2017) argument, that past behaviour and habits are important for explaining transportation choices. With that said, the pseudo R^2 statistics which coincidentally increased by the same amount (.013) for step III and step IV, suggest that bike ownership is contributing more in explaining interest levels. This is indicated by the fact that bike ownership, being the only new significant variable added in the third step, contributed equally much as the two significantly added variables in the fourth step.

Moreover age has a consistent and relatively strong effect on stating interest. This is indicated by the stable coefficient values and z-scores. The effect of environmental consciousness has decreased marginally during the steps and has been consistently strong throughout the steps. The results from this final step suggest that stating interest in participation might be more a reflection of green values as well as being familiar with cycling than daily mobility patterns. It is worth noting that the assumption of parallel lines in ordinal logit models is not violated, a benefit for the validity and reliability of the results.

Table 4.2: Results from ordinal logit models with stated interest in bikesharing participation as dependent variable.

	Step I		Step II		Step III		Step IV	
	Coef.	(Z-Scores)	Coef.	(Z-scores)	Coef.	(Z-scores)	Coef.	(Z-scores)
Individual characteristics								
Female (ref. male)	.029	(.074)	-.113	(-1.079)	-.106	(.945)	-.088	(.643)
Age	-.031	(65.624)***	-.032	(67.796)***	-.034	(68.501)***	-.032	(60.523)***
Higher education (ref. lower education)	.323	(7.285)**	.218	(3.232)*	.178	(2.110)	.145	(1.383)
Higher income (ref. lower)	.002	(.000)	-.005	(.002)	-.094	(.541)	-.069	(.289)
Attitudes								
Economic orientation			.072	(2.368)	.054	(1.308)	.060	(1,582)
Environmental consciousness			.228	(33.764)***	.216	(29.109)***	.195	(23.049)***
Urban outlook			.016	(.263)	.033	(1.024)	.021	(.401)
Urban form and transportation resources								
Population density					.006	(.055)	.004	(.031)
Building use diversity					-.407	(1.317)	-.386	(.436)
Bærum (ref. Oslo)					-.186	(1.397)	-.050	(1.178)
Log. distance to public transport					-.050	(.086)	-.008	(.085)
Access to car (ref. no access)					.008	(.004)	.102	(.618)
Bike ownership (ref. no bike)					.453	(13.515)***	.363	(7.732)***
Daily mobility pattern								
Public transportation frequency							.081	(3.878)**
Public transport user (ref. other)							.216	(1.142)
Public transportation user and cyclist (ref. other)							.507	(5.268)**
Cyclist (ref. other)							.202	(.466)
Model fit								
Nagelkerke R^2		.064		.093		.106		.119

p<0.01***, p<0.05**, < 0.1 *

4.3 ACCESS AND USE OF PUBLIC TRANSPORTATION AND HOW THIS AFFECTS ACTUALLY REVEALED MEMBERSHIP CHOICE

4.3.1 Model interpretation

A Binary logit regression is used to analyse actually revealed membership choice in Oslo and Bærum. The model has a similar stepwise model build-up as the models in Table 4.2, having four steps where the same variables are included, with the exception of bike ownership, which was omitted. The variable was omitted because all bikesharing members in the sample owned a private bike and the variable impacted the model in its whole in form of large standard errors. The Nagelkerke R^2 value is also presented for each step in the table, signifying the overall explanatory power for each step in the model.

The main difference from the ordinal regression is that the dependent variable is dichotomous; making the interpretation somewhat easier as the coefficients give the log odds of being in one of the two categories (Field, 2018). Either you have a bikesharing membership or you do not. Coefficients with values above zero indicate that an increase in the independent variable's value contributes to an increased likelihood of having a bikesharing membership (Garson, 2016). Contrariwise, negative coefficient values indicate that an increase in the independent variable is decreasing the probability of having a bikesharing membership. The same significance levels of 90, 95 and 99 percent are used in the binary logit models.

4.3.2 Step I - Effect of individual characteristics

From the results presented in the first step in the model in Table 4.3 there are some obvious similarities to the individual characteristics presented in the first step in Table 4.2, since age and education are also affecting actually revealed membership choice. The association between age and membership is strong and negative. A one unit increase in age is associated with a -.073 log odds of not having a membership. In line with the descriptive results and literature the results from the model show an association between higher education and increased probability of not only stating interest in participating in bikesharing, but also of revealed membership choice (Fishman et.al., 2013; Shaheen, 2011). The insignificant results of gender and income are however unexpected in light of the literature review, as membership in other cities to a large degree are associated with differences in income and gender (Adams et.al., 2017). Whether this is a reflection of smaller income- and gender- inequalities in Oslo and Bærum or if it is just a random trait of this specific sample is however not clear.

4.3.3 Step II - Effect of attitudes

By adding the attitude variables in the second model, the pseudo R^2 value increases from .128 to .175 thus adding explanatory value to the model. It is first when controlling for attitudes that gender becomes significant and reveals that there are differences between males and females; being female decreases the probability for having bikesharing membership. This result is in line with the literature presented in the theory chapter (Liu et.al. 2012; Adams et.al., 2017). This could be explained by the effect gender has on attitudes, especially environmental attitudes (Hampel et.al. 1996). The effect is however relatively weak compared to the coefficient values of the continues variables age, environmental consciousness and urban outlook, which also are significantly associated with revealed bikesharing membership.

Economic orientation is negatively affecting bikesharing membership. The significance level is however on a 10 percent level and some caution should be taken when interpreting this result as it is a higher chance that the result is random (Ringdal, 2013). In contrast to stating interest urban outlook is significantly and positively effecting revealed membership choice. This might however be a result of urban living conditions, an aspect that will be controlled for in the next section.

4.3.4 Step III - The effect of urban form and transportation resources

In the third step urban form- and transportation resource- variables are added, taking away the effect of economic orientation. The overall explanatory power of the model increases demonstrated by the pseudo R^2 statistic that changes from .175 to .226. The model shows that population density, log. distance to public transportation and access to a car are significantly affecting revealed membership choice.

Interestingly the significant results from this step are different from the variables affecting stated interest in bikesharing participation. In comparison population density is associated with a higher log odds of having a bikesharing membership, being in line with previous research on bikesharing membership (Bachand-Marleau & El-Geneidy, 2012). The result is also consistent with literature on transportation choice, as density is associated with choosing transportation modes like walking and cycling (Ewing & Cervero, 2010). In comparison to stating interest access to car is negatively affecting the probability for bikesharing membership. A negative association between car access and bikesharing membership supports the hypothesis that people who do not own cars are reliant on a broader mix of transportation modes, bikesharing amongst others. From a time geographic perspective it might be explained by bikesharing's potential to lift spatial constraints in certain daily mobility contexts.

The logarithmic distance to public transportation is negatively affecting bikesharing membership. That the distance is logarithmic implies that it is measuring the relative distance between residence and closest public transportation stop. The regression was also run with normal distance, but this had no effect on bikesharing membership, illustrating that the relative distance is more important than actual distance. The effect implies that living further away from public transportation reduces the probability of having a bikesharing membership, a suggestion that connectivity to public transportation is affecting bikesharing integration in daily mobility. This result is consistent with Bachand, Lee and El-Genedy (2012) results. Interestingly there is no significant difference between Bærum and Oslo in likelihood of having a bikesharing membership. Furthermore the building use diversity does not have an impact on revealed membership choice. These are two variables I would, based on the literature review, believe to impact the probability of revealed membership choice (Ewing & Cervero, 2010; Mateo-Babiano et.al., 2016). This might be a result of bikesharing facilitates use in other areas than residential neighbourhood.

As expected, when controlling for urban form the effect of urban outlook has decreased substantially, the variable does however indication that bikesharing might be linked to preferring an urban lifestyle. Furthermore, recalling the literature review, it is interesting that the effect of environmental consciousness decreased significantly, when adding the urban form and transportation resources variables. Kahn & Morris' (2009) findings suggest for instance that there is a correlation between environmental consciousness and choosing to live in urban areas, indicating an intermediary effect between environmental consciousness, urban form and bikesharing.

Interestingly, the urban form variables from this step demonstrates that geography matters for membership choice. This can be explained by many factors, though it can seem like bikesharing membership is linked to certain opportunities and constraints related to the urban form of residential neighbourhoods. Using a time geographic approach it may seem that bikesharing is most relevant for increasing individuals' *potential path area* in dense and connected areas. This might also explain the relatively high and negative effect of car ownership, as car owners might not be reliant on multiple transportation resources in order to increase their space-time prism.

4.3.5 Step IV - The effect of daily mobility pattern

In the final model the daily mobility pattern variables are added and the overall explanatory power expressed by the pseudo R^2 value increase from .266 to .331. The final model illustrates that age, urban form, car access and combining transportation modes in daily mobility are important in explaining membership choice.

An interesting result from the fourth step is that gender is no longer significantly associated with revealed membership choice. The previous steps indicate a higher probability for males to have a bikesharing membership compared to females. By adding the daily mobility variables the results show that much of the gender differences are controlled for by having a different daily mobility mix; a strong suggestion that there are differences in the daily mobility pattern of men and women.

In comparison to the fourth step in table 4.2, public transportation frequency is not significantly associated with having a membership. Thus, there is no essential difference between non-members and members in terms of being a frequent user of public transportation. A daily mobility pattern which consists of both cycling and public transportation is however associated with bikesharing membership. This relationship was also found to be associated with higher interest levels, something that is relevant to the hypothesis. The results from Table 4.3 indicate that it is a higher probability for people who combine cycling and public transportation to have a bikesharing membership compared to the reference group of drivers and pedestrians. This result could of course be endogenous as bikesharing members might be combining bikesharing and public transportation in their daily mobility pattern as a result of their membership. With that said it is uncertainty linked to whether the respondents used a bikesharing bike or a private bike since it was no distinction in the survey question. However, as a similar mobility pattern was found by non-members it suggests that it is the habit of combined travel that explains the association. This explanation is also in line with other studies where combined cycling and transit has been used to investigate bikesharing membership (Bachand-Marleau & El-Geneidy (2012). The result is however important in light of the research question as it suggests that bikesharing and public transportation is being integrated in daily mobility in Oslo and Bærum.

Table 4.3: Results from binary logit models with revealed membership choice as dependent variable.

	Step I		Step II		Step III		Step IV	
	Coef.	(Z-Scores)	Coef.	(Z-scores)	Coef.	(Z-scores)	Coef.	(Z-scores)
Individual characteristics								
Female (ref. male)	-.242	(2.230)	-.366	(4.713)**	-.458	(6.703)**	-.228	(1.470)
Age	-.073	(63.990)***	-.074	(62.580)***	-.053	(31.969)***	-.051	(27.265)***
Higher education (ref. lower education)	.556	(7.980)***	.483	(5.587)**	.451	(4.589)**	.493	(4.972)**
Higher income (ref. lower)	-.192	(.893)	-.141	(0.460)	.245	(1.150)	.151	(.525)
Attitudes								
Economic orientation			-.128	(3.217)*	-.074	(967)	-.108	(1.836)
Environmental consciousness			.245	(14.342)***	.157	(5.338)**	.061	(.731)
Urban outlook			.244	(20.600)***	.121	(4.901)**	.100	(3.114)*
Urban form and transportation resources								
Population density					.172	(24.471)***	.173	(23.075)***
Building use diversity					.668	(1.561)	.828	(2.170)
Bærum (ref. Oslo)					-.754	(1.962)	-.787	(2.073
Log distance to public transport					-.789	(4.628)**	-.710	(3.639)*
Access to car (ref. no access)					-.719	(13.110)***	-.668	(10.523)***
Bike ownership (ref. no bike)					-	-	-	-
Daily mobility pattern								
Public transportation frequency							.038	(.388)
Public transportation user (ref. other)							-.016	(.001)
Public transportation user and cyclist (ref. other)							1.408	(8.352)***
Cyclist (ref. other)							.216	(.080)
Model fit								
Nagelkerke R^2	.128		.175		.266		.331	

p<0.01***, p<0.05**, < 0.1 *

4.4 CONCLUDING DISCUSSION

The results from the descriptive relationships suggest more similarities between stating interest in participating in bikesharing and bikesharing membership. These results suggest that not having access to a car, using public transportation frequently and combining cycling and public transportation would be associated with interest and membership. Only combined usage of public transportation and cycling was related to stating interest as well as having a bikesharing membership. This shows the importance of regression models where individual characteristics, attitudes and urban form can be controlled for, in order to saying anything substantial about the relationships (Rubin, 1985).

From the results presented in this chapter I can conclude that people’s transportation resources and daily mobility patterns are only to a certain degree affecting stating interesting in participating in bikesharing. Bike ownership is for instance the only transportation resource with an association to higher interest levels. Aspects like not having access to a car, being connected to transit or living in Oslo have no effect on interest levels. With that said the results show that an increase in trips taken by public transportation is linked to a higher probability of stated interest in bikesharing membership. Moreover and consistent with previous studies, existing habits of combining cycling and public transportation have a relative high effect on stated interest (Lanzini & Khan, 2017).

Nevertheless some of the control variables seem to be more important in explaining why some people state to be interested in participating in bikesharing compared to others. Not surprisingly age is impacting being interested, as age is related to different capability and coupling constraints which can enable and limit the attractiveness of transportation modes. Additionally, stated interest in participation is to a large degree effected by environmental consciousness. The effect of being environmentally conscious is in fact larger than the effect of daily mobility patterns and transportation resources. Stating to be interested in bikesharing could therefore be more of a reflection of green attitudes than having an intention of actually participating in a bikesharing program.

There are however some key similarities between bikesharing members and the respondents who state to be interested. They are young, educated, have a habit of combined travel and are environmentally conscious. These are all traits of early adopters (Shaheen et.al., 2011). It is however interesting that only some people actually adopt bikesharing. Differences between the significant independent variables of bikesharing interest and membership might therefore give further insight into factors that are important for integrating bikesharing in daily mobility.

There are notable differences between the variables that are affecting stated interest and actually revealed membership choice. Urban form and transportation resources have for instance a considerable effect on revealed membership choice. Owning a car decreases the chance of having a membership, in addition distance to public transportation is associated with having a bikesharing membership. Living close to public transportation suggests that connectivity is important for integrating bikesharing and public transportation in daily mobility. As distance to bikesharing stations is not controlled for, this result could however also be a reflection of living close to well connected areas. The results also imply integration between public transportation and bikesharing, since combining cycling and public transportation is associated with a relatively higher log odds of membership.

Understanding these results in the context of time geography it seems like integrating bikesharing with public transportation in daily mobility is linked to opportunities and constraints related to urban form as well as transportation resources. People living in dense and well-connected areas might have fewer spatial constraints in the form of long travel distances, making bikesharing a beneficial transportation mode (Ewing & Cervero, 2001). The results can be understood as a consequence of bikesharing members combining transportation modes in daily mobility as a means to cover transportation needs, increasing their space time prisms.

Environmental consciousness is to a much smaller degree affecting actually revealed membership choice in comparison to stating interest. This indicates that membership choice is more likely to happen when bikesharing is practical and when it can fill a transportation need. This finding suggests that bikesharing membership is to a small degree based on green values and illustrates that there is a clear distinction between stating interest in participating in bikesharing and taking an actual membership choice. The results suggest that stating interest in sustainable transportation might rather be a reflection of green values than an actual intention of becoming a member. Revealed membership choice however is more classically explained as a manifestation of travel.

The results from this chapter are consistent with previous studies and illustrate the difficulties of acting according to environmental beliefs (Kennedy, Beckley, McFarlane, & Nadeau, 2009; Lanzini & Khan, 2017). This could also explain some of the descriptive results where there were no obvious differences of respondents who have access to less sustainable transportation modes, like a car, in stating high levels of interest in bikesharing participation. The results from this chapter indicate that walking the talk is not an easy task with regard to sustainable travel, and bikesharing membership is rather a result of opportunities and limitations presented by urban form, transportation resources and daily mobility patterns, rather than environmentally friendly attitudes.

In line with the hypothesis the results suggest that bikesharing integration in daily mobility seem most apparent for people who already use a broad mix of transportation modes in their daily mobility pattern. Urban living both in Oslo and Bærum, connectivity to public transit and not having access to efficient modes of transportation, like a car, increases the probability of integrating bikesharing in daily mobility. Bikesharing integration in daily mobility might therefore seem most apparent for people who already use a broad mix of transportation modes in their daily mobility pattern.

5 RESULTS PART II

Integrating bikesharing with public transportation on individual journeys

The aim of this chapter is to see whether bikesharing is being integrated with public transportation on individual journeys in form of access and/or egress trips to or from metro- and railway- stations in Oslo. To do this will I address RQ2:

What impact has connectivity to public transportation, along with other urban form aspects at bikesharing origin and destination stations, on bikesharing route frequencies?

The chapter is built up of two key sections. The first is descriptive, presented in maps and graphs. Maps have been used to explore bikesharing mobility patterns visually giving further insight into the geographic materialisation of bikesharing in Oslo. In the second part of the chapter the results from the negative binomial regressions are presented. Urban form at start and end station, as well as route characteristics, are controlled for in the models, demonstrating the effect connectivity to the metro- and railway- system has on bikesharing route frequencies.

I will not view the effect of connectivity to the public transportation system in its whole in this chapter as it has proven to be problematic in two ways. Firstly, nearly all bikesharing stations will be in proximity to a public transportation stop. Bus stations are for instance generally placed within 400-500m of each other (Sandberg, 2015). Routes that are not connected to public transportation will therefore most likely be a reflection of areas that are used seldomly. Secondly, the number of public transportation stops make it highly difficult to control for the station environments in the regression models. Studying the metro- and railway- system is however highly interesting, as the system has proven to be important for bikesharing in other cities (Lansell, 2011; Griffin & Sener, 2016). Railway systems have fewer stops and are highly efficient transportation modes and bikesharing might therefore be used in combination with the system. Viewing bikesharing integration with metro and railway stations is therefore not only possible, but also of theoretical relevance.

The hypothesis related to RQ2 is built on previous findings regarding bikesharing integration with metro- and railway- system on individual trips. As previous studies have found that bikesharing might serve an important integrational purpose with the metro and railway system, I expect similar findings in Oslo (Ji et.al., 2017). If this is the case, routes that are connected to a metro- or railway- station at one end of the route will be associated with higher route frequencies than unconnected routes. Furthermore there will most likely be spatio-temporal variations in the mobility pattern, being a reflection of the daily commuter pattern. It is therefore likely that morning routes are associated with egress trips from a metro/railway station. Conversely I expect that afternoon route frequencies are associated with access trips to metro/railway stations.

5.1 DESCRIPTIVE RESULTS

5.1.1 How to read the maps

Maps have been created for the purpose of illustrating travel patterns by the Oslo City Bike. The scale of the maps were set to 1:62 000 in order to cover the whole study area. The maps in Figure 5.1 and 5.2 were created to show spatio-temporal variation in station usage, with especial focus on commuter patterns. This has been done by viewing the total sum of station frequency during morning and afternoon hours. In addition it is interesting to see how station frequencies are related to urban form. The statistics on grid cells presented in the methods chapter are therefore used as a map layer demonstrating each cell's population and employment density. The size and colour of the bikesharing stations indicate the sum of morning usage frequency and afternoon usage frequency. To display and classify the data natural breaks have been applied. The intervals in this classification method is uneven, as the intervals are selected where large changes in value occur displaying variety within the data (Smith et.al 2018).

The map in Figure 5.3 and 5.4 illustrates routes frequently used by bikesharing and is a result of network- and line density- analysis and the scale is set to 1:60 200 and 1:35 000. Recalling the methods chapter the routes are built on a route analysis made in ArcMap. The routes are thus an illustration of the shortest path between two bikesharing stations (Mitchell, 2012). There are two major shortcomings with this method. Firstly, people tend to not always be aware of the shortest route and may unknowingly take detours. Secondly, other aspects are also taken into consideration when choosing which route to take (Hulleberg et.al 2018). Safety, infrastructure and even aesthetics can be decisive in the choice. The routes in the maps are therefore not necessarily an accurate representation of how the routes were cycled, but it gives a good indication of where people are using bikesharing in Oslo.

An open street map layer was used taking junctions and edges into the calculation and the map shows the shortest routes between the station (Esri, 2015). A line density analysis was used in ArcMap to demonstrate the routes with high frequencies and the output from the analysis is a raster feature. The line density analysis calculates the density of linear features, in this case routes, in the neighbourhood of each raster cell (Esri, 2016).

Density is calculated in units of length per unit area. The unit area is set to $25m^2$ around each cell. Conceptually this is done by a circle being drawn around each raster cell's centre using the $25m^2$ search radius (Esri, 2016). The length of the portion of each line that falls within the circle is multiplied by its population field value, in this case route frequency, the figures are then summed and divided by the circle's area on $25m^2$. It is worth noting that in many cases different routes will run along the same path and together add high values, an indication that the chance of meeting a person on a bikesharing bike along some paths is relatively high compared to other roads.

Natural breaks were used in this analysis to classify the data. Darker and saturated colours represent routes with high values and signifies that a route is frequently biked. Conversely lighter colours represent low value routes and illustrate that a path is used less frequently.

5.1.2 Station frequencies

Bikesharing station frequencies displayed in the maps in Figure 5.1 and Figure 5.2 illustrate a daily spatio-temporal mobility pattern. The maps show the sum of morning- and afternoon-station frequencies and the aggregated behaviour of the users reveal some general trends in bikesharing usage. The spatial illustration of station frequencies demonstrates how the travel pattern is related to the urban form in Oslo, as literature has pointed to urban form impacting travel behaviour (Ewing & Cervero, 2010; Liu et.al., 2012). Since the maps are based on population data the descriptive results illustrate how bikesharing is being used in Oslo.

The maps reveal a distinct mobility pattern during the mornings as origin station activity is high in residential areas and end station activity generally occurs in areas with high employment density. Areas linked to high population density like the neighbourhoods St.Hanshaugen, Günerløkka, Sagene and Tøyen have for instance a high start station activity. The city centre, which has a low population density, is on the contrary linked to lower start station frequencies, with the exception of a few bikesharing stations in especially central locations. Bikesharing stations in proximity to the main metro- and railway- stations in Oslo have for example high station frequencies and can indicate that the bikesharing stations are used for egress trips.[8]. End station activity on the other hand is most apparent in areas with high employment density like the inner-city centre, Skøyen, Majorstuen, and to a lower degree Nydalen.

A sign of a distinct mobility pattern during the morning is that there are few stations that function both as origin and destination station, with the exception of a few bikesharing stations in the inner-city, particulary at Aker Brygge and Nationaltheateret. This pattern however changes during the afternoon as a considerable amount of start stations in the city centre also have relatively high end station frequency, indicated by the map in Figure 5.2. This pattern suggests that mobility is more flexible and varied during the afternoon. Especially stations by Aker Brygge and Tjuvholmen, an area by the waterfront with diverse land use, seem to be a frequent origin and destination during afternoon hours (Aker brygge, 2019).

Furthermore variety in afternoon trips is demonstrated by station activities in areas associated with low population- and employment- density. For instance trips also start in areas that are linked to recreational activities, at for example Bygdøy, in contrast to morning trips where nearly all trips start or end in areas linked to employment and dwellings. The bikesharing station at Sukkerbiten, the closest stop to Sørenga, also experiences high start- and end- station activity during the afternoon. This area lies in a central location, but compared to surrounding areas the population and employment density is lower. The high afternoon frequency may therefore rather be explained by the varied land use in the area, as Sørenga has a mix of flats and restaurants in addition to recreational land use (Ewing & Cervero, 2010).

The aggregated bikesharing behaviour illustrated in the maps indicate a spatio-temporal mobility pattern. The mobility pattern can be understood in light of time geographic constraints in the context of urban form. Hägerstrand (1985) argues that one of the biggest time geographic constraints is the need to leave the home in order to fulfil daily projects for so having to return after a certain amount of time. The principle of return has impacted how we organise our society, also in terms of working hours, and this may manifest itself in commuter patterns.

[8] Referring to the metro- and railway- stations at the Central Station in Oslo and the Nationaltheatret.

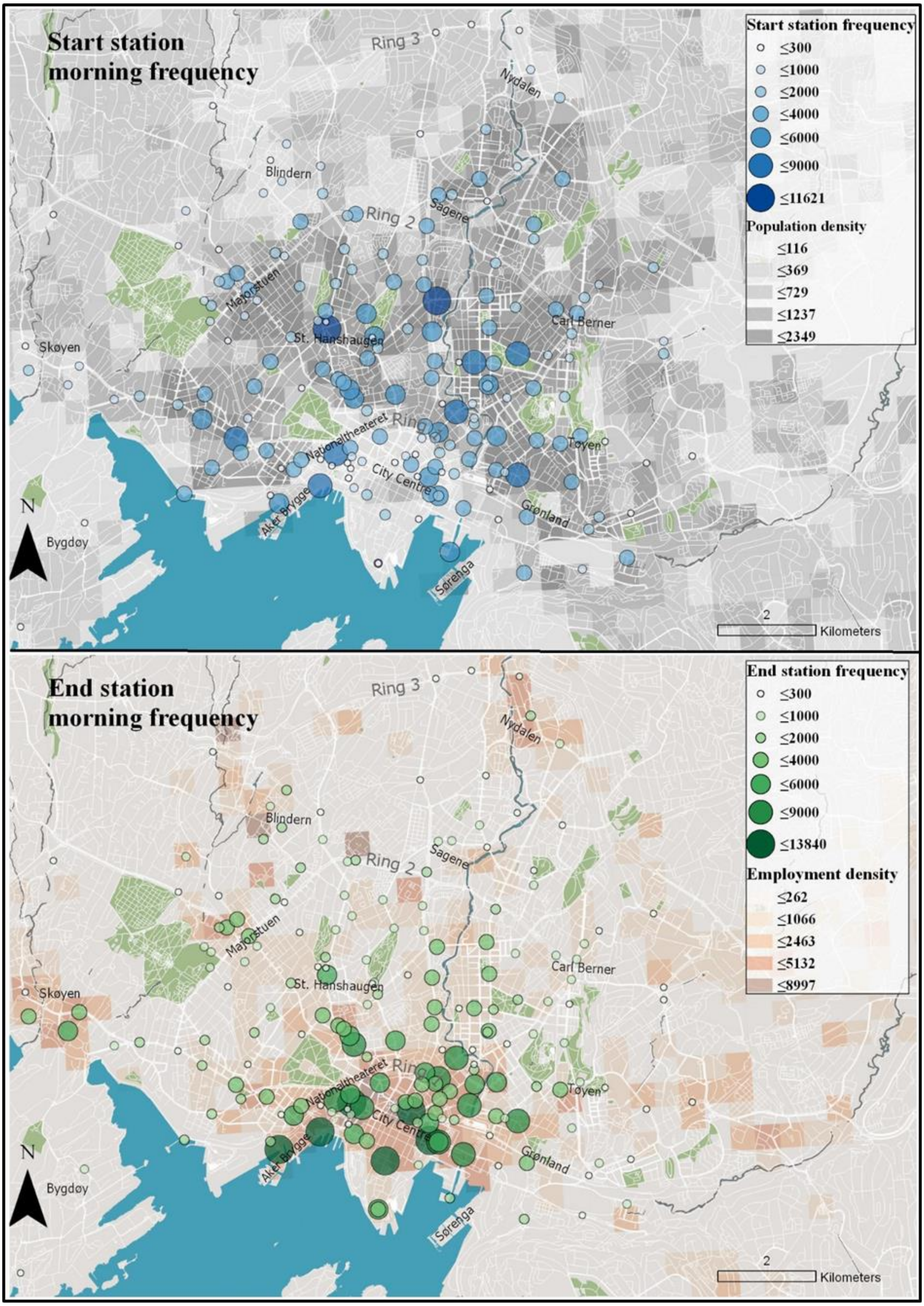


Figure 5.1: Map showing the number of times bikesharing stations have been used as start- and end- station during the time period 06:00-09:00 during weekdays. The station frequencies are illustrated in relation to the urban form of the city. Source: Kartverket 2017, SSB 2017

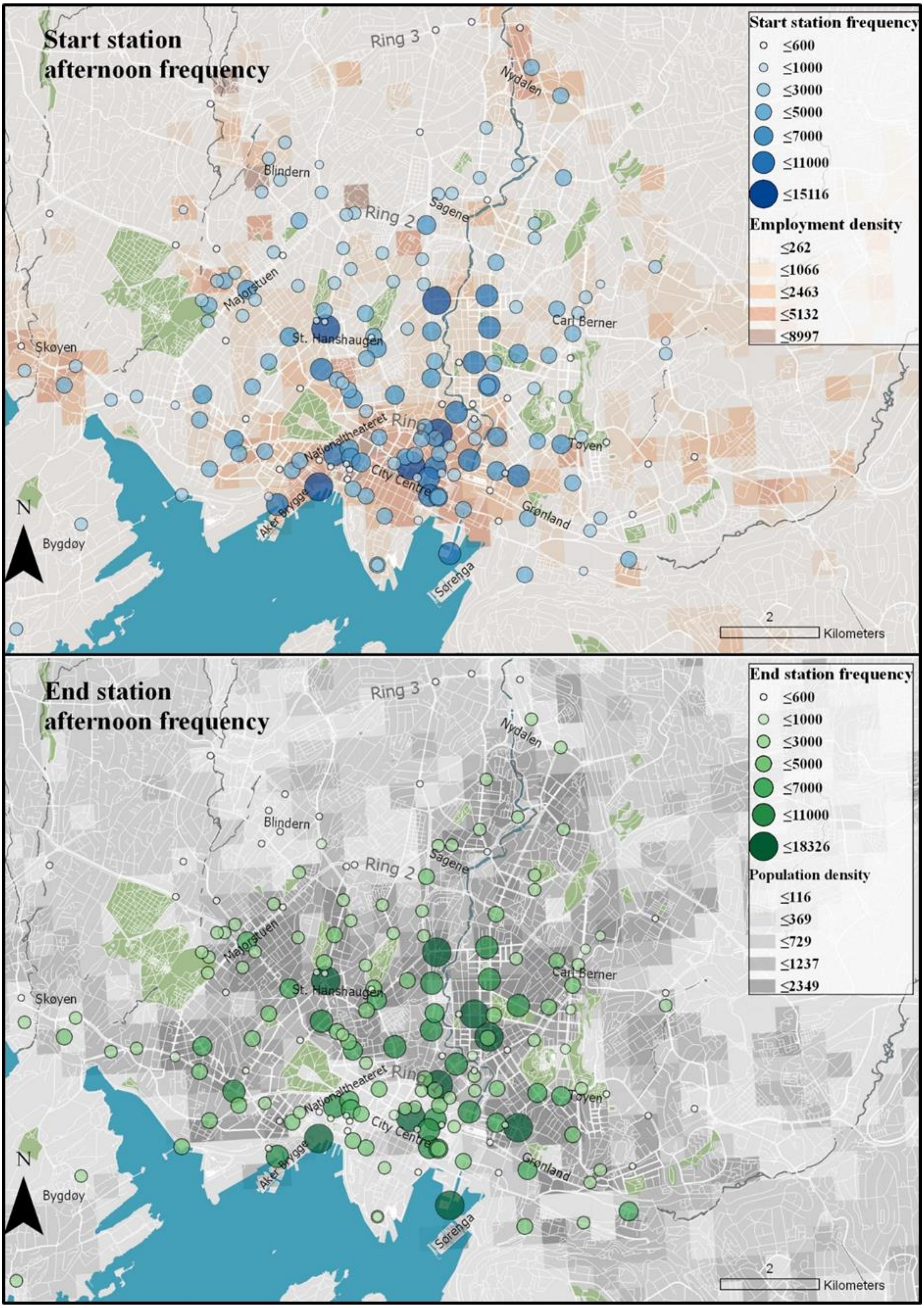


Figure 5.2: Map showing the number of times bikesharing stations have been used as start- and end- station during the time period 15:00-18:00 during weekdays. The station frequencies are illustrated in relation to the urban form of the city. Source: Kartverket 2017, SSB 2017

The distinct commuter pattern during the morning strongly suggests that morning hours are related to more time geographic constraints. Coupling constraints may for instance be more apparent during the morning hours as people need to join others at work during a certain time period in order to fulfil common projects (Miller, 1991). Moreover, as many people are starting in the same residential locations, this aggregated travel behaviour can put pressure on the transportation system in its whole. During the afternoon, when people tend to have more time, and less constraints, the mobility pattern changes, showing a more varied mobility pattern. This is also suggested by the higher station-frequency numbers during the afternoon, compared to the mornings.

The physical surroundings also enable or restrict certain travel behaviour (Næss, 2015). There are for example areas with high employment density, outside the immediate city centre where station frequencies are much lower, with the exception of Skøyen. This may be explained by lower degrees of connectivity which previous studies on bikesharing has pointed out as important reasons for lower ridership levels (Fishman et.al 2013). Furthermore distance may play a part, being a capability constraint in terms of exertion, as well as an urban form characteristic linked to lower levels of cycling (Næss, 2006).

5.1.3 Route frequencies

The previous maps show bikesharing station frequencies, but the maps tell nothing about how the routes are biked. Compared to other transportation modes where routes often are fixed, bikesharing is a highly flexible transportation mode in regard to route choice as only the origin and destination station are established points on the route. The maps in the figures 5.3 and 5.4 give a general indication of how the routes between bikesharing stations are being cycled, even though route choice may differ considerably in reality. Railway and metro stations are added to these maps to show how route frequencies may be related to public transportation accessibility.

The line density analysis in the maps in Figure 5.3 and Figure 5.4 suggests that routes close by central metro- and railway- stations have especially high frequencies. Notably high are the route frequencies in close proximity to Oslo S and Nationaltheateret. The same tendency is shown for Skøyen, Majorstuen, Nydalen and to a certain degree Tøyen, which are all connected to either metro or railway stations[9]. This suggests that connectivity to efficient public

[9] See previous maps for spatial references.

transportation modes, like the metro- and railway- system, may be related to increased bikesharing route frequencies.

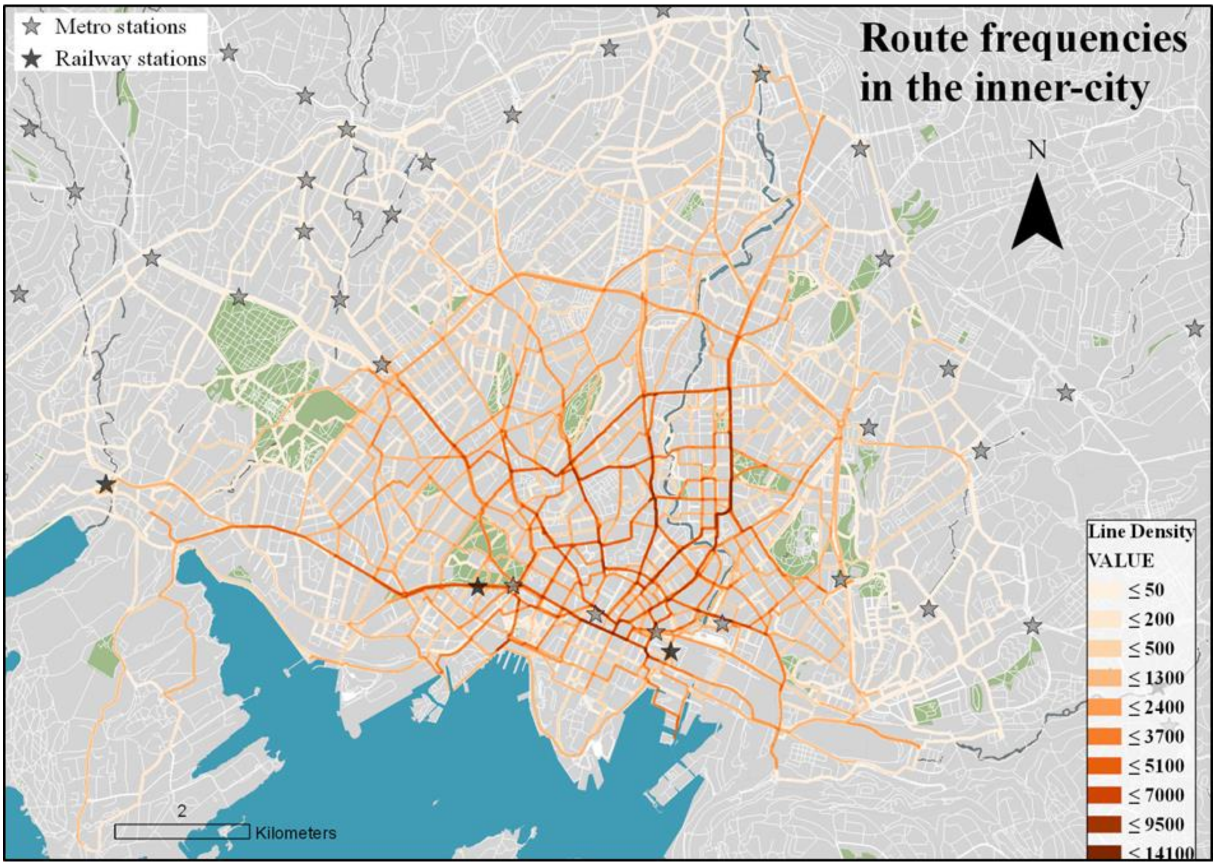


Figure 5.3: Line density analysis illustrating route frequencies in relation to metro- and railway- stations. The values demonstrates the calculated route frequencies of each raster-cell.
Source: Entur 2017 & Kartverket 2017

The map in Figure 5.4 has its scale reduced to 1:35 000, revealing variety in the mobility pattern of bikesharers in the inner-city. In line with previous literature most bikesharing activity is found in the city centre, illustrating that the bikes are not used for very long distances (Zhang et.al., 2017). In fact the mean route distance is just above 2.7 km for the Oslo City Bike. The map suggests that paths that are connected to metro/railway stations have high frequencies. If the trip actually starts by a metro- or railway station is however unknown, but the map can contribute with some general indications. Routes going to/from waterfront areas have for example especially high route frequencies. From the maps it seems like many of these routes start or end at bikesharing stations close to metro/railway stations at Nationaltheateret and Oslo S. With that said there are also a few areas not connected to a metro- and railway- station which feature high route frequencies. Route frequencies by Sagene and Grünerløkka are for instance high. In such cases bikesharing may be used to increase the access of the public transportation system, by offering an alternative transportation mode to/in areas that are not connected to the metro/railway system (Ji et.al. 2018).

In line with the station frequency maps, do the line density analysis demonstrate that route frequencies are lower outside the inner-city. This can be due to the urban form characteristics outside the city centre as well as fewer bikesharing stations in these areas (Castillo-Manzono et.al.,2016; Liu et.al., 2012). High route frequencies are found between the Majorstuen metro stop and the city centre. This can suggest that many trips either start or end at this metro station and may be used for access/egress trips. A shortcoming of the line density results is that the direction of the route is not displayed in the map. Saying if the bikesharing routes are in any way integrated with metro/railway in terms of access or egress trips is therefore not possible from this descriptive analysis.

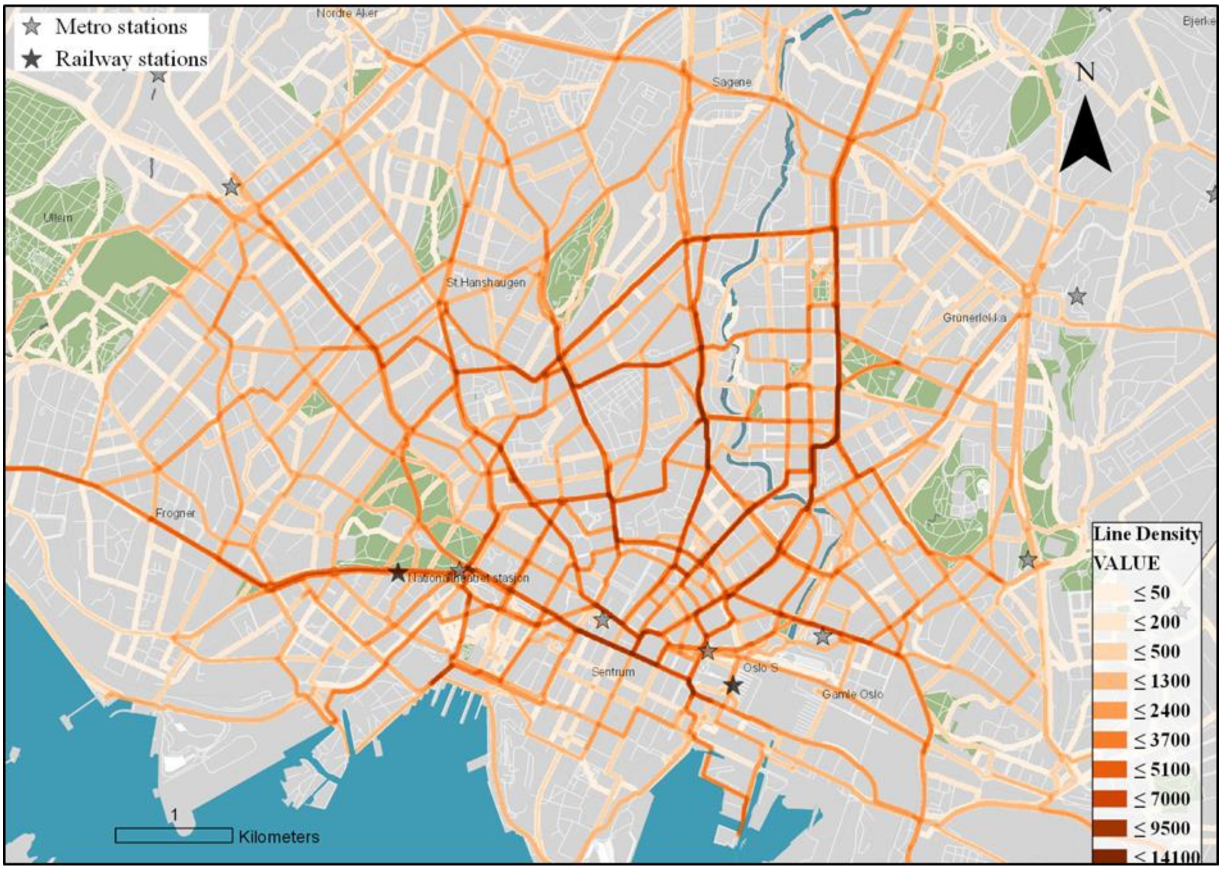


Figure 5.4: Map showing route frequencies in the city centre in relation to metro- and railway- stations. Source: Entur 2017 & Kartverket 2017

5.1.4 Connectivity to metro or railway station on route frequencies

The graph presented in Figure 5.5 gives a general indication of which role connectivity to metro/railway has on bikesharing route frequencies. Bikesharing routes that are connected to a metro or railway station at one end of the trip have routes with higher mean frequencies. The graph suggests that this is especially the case for routes that are connected to metro/railway at the destination station. The connectivity variation where bikesharing is connected to a metro or railway station within 200m of the origin or destination station in the route suggests that substitution is not happening to a large degree in Oslo. Most importantly the graph shows that routes that are connected to metro/railway stations have higher mean frequencies than routes that are not connected, being in line with results from other cities (Shaheen et.al., 2011; Ji et.al., 2018). This trend may however be explained by the central locations of the transportation modes instead of proximity to bikesharing stations.

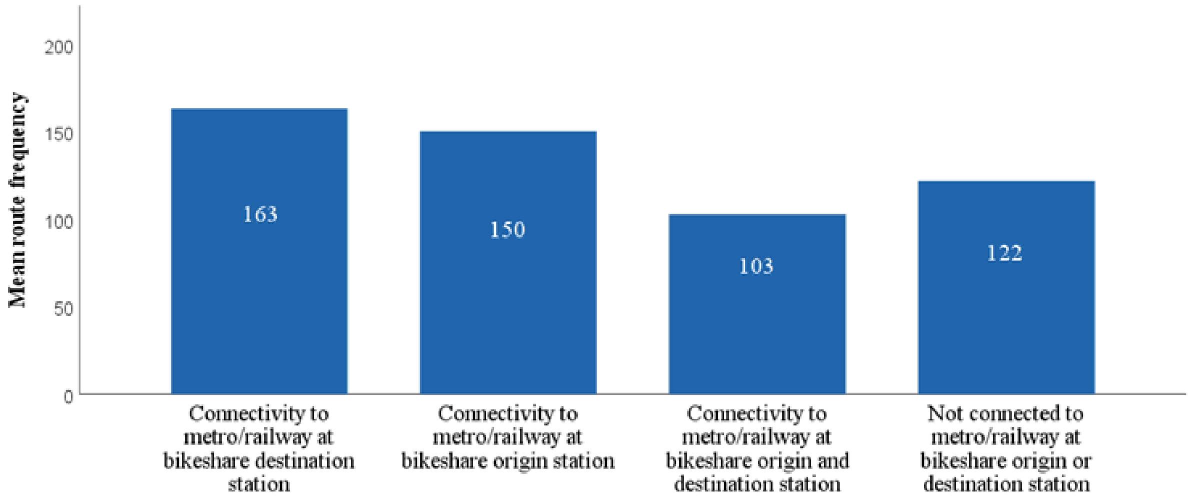


Figure 5.5: Mean route frequency for connectivity variations between bikesharing stations and metro- and railway- stations

The graph in Figure 5.6 shows the mean frequency of routes taken during the morning- and afternoon- peak representing commuter trips. The graph shows that mean route frequencies are generally higher during the afternoon hours, again suggesting flexibility and variety of trips taken during the afternoon. Routes that are connected to a metro/railway station at the destination end of the trip have however the same mean frequency for both morning and afternoon trips. Opposite to the hypothesis the graph suggests that morning trips are related to accessing public transportation, whereas afternoon trips seem to be related to egressing metro-and railway stations. Additionally the mean route frequency is relatively high for unconnected routes during the afternoon hours. This may be a result of more recreational trips or the need to access different types of locations.

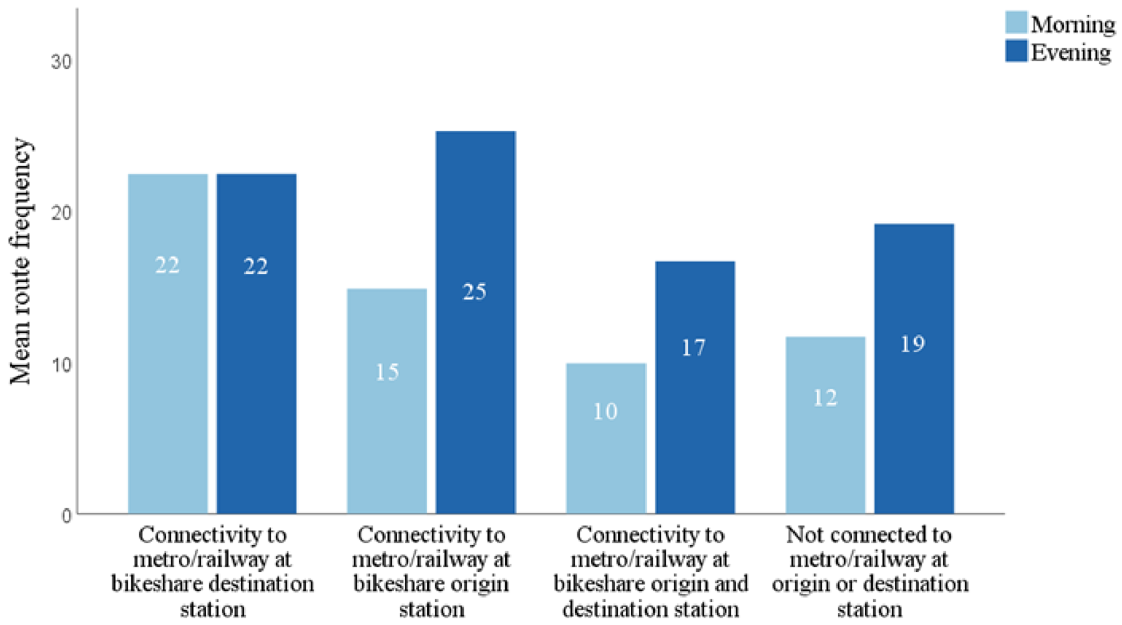


Figure 5.6: The mean route frequency for different connectivity variations between bikesharing origin and destination station and metro- and railway- stations

5.1.5 Summing up the descriptive relationships

The maps and graphs in this section have illustrated variety within the dependent variables in addition to illustrating bikesharing mobility pattern in Oslo in relation to spatio-temporal patterns and connectivity to metro and railway stations. A weakness of the descriptive analysis, even when using population data, is that it cannot say anything about whether connectivity to public transportation is significantly associated with higher route frequencies (Rubin, 1985). To say something substantial about this topic it is necessary to see the effect of connectivity separately from other urban phenomena which can also be affecting the route frequencies. Without controlling for station environments and route characteristics the analysis will fall short in explaining bikesharing integration with the metro- and railway- system on individual trips (Liu et.al., 2012). Therefore, in the next section urban form characteristics in the bikesharing stations' local neighbourhoods, in addition to the nature of the route, will be controlled for, making it possible to discover the effect of connectivity to metro and railway stations on route frequencies.

5.2 THE EFFECT OF PUBLIC TRANSPORTATION CONNECTIVITY ON ROUTE FREQUENCY

5.2.1 Model interpretation

As in the previous results chapter the results will be presented in a stepwise model build-up where the direction and strength of the new variables added to the model will be interpreted. The first step in Table 5.1 include the control variables measuring route distance and elevation between start and end station. In the second step variables measure urban form characteristics at origin and destination station added. These variables are population density, land use diversity and centrality. Furthermore the number of locks at the station is added. Together the variables from the first two steps control for urban form characteristics at origin and destination station as well as route characteristics, enabling the effect of connectivity to metro/railway to be measured in the third and final step of the model-build up.

The regression was run in Stata and the default R^2 statistic is the Mcfadden's pseudo R^2. The pseudo R^2 varies from 0 to 1 and values and a score between .2 - .4 indicate a good model fit (Giselmar et.al, 2016). With that said R^2 values are expected to be low for studies on individual travel behaviour as R^2 values are normally between .02-.08 (Ferrer & Ruiz, 2013).

The NBR model coefficients demonstrate how one unit increase/decrease on the independent variables indicate the change in expected log count of the bikesharing routes (Cameron & Trivedi 1998). Put differently, positive coefficient values are linked to higher expected route counts, whereas negative coefficient values indicate lower expected route frequencies.

The Wald-test, represented by the Z-score is used to test null hypothesis. Here the null hypothesis is that the coefficients are equal to zero (Field, 2018). High z-scores indicate that the coefficients are different from zero whilst the p values signify the statistical significance of the Z-scores. The conservative significance levels for the models are set to 95, 99 and 99.9 percent. As I am working with population data it is likely to be much variation among the observations and significant results are therefore expected (Gordon, 2016). This is usually regarded as a huge advantage, but as even small differences between the variables can result in significant results it is a risk of getting type I errors – rejecting a true null hypothesis. The Z-scores become especially important for the interpretation, as higher scores indicate high degrees of variations between the observations.

5.2.2 Step I – The effect of route characteristics

Step one of the analysis shows that the coefficients work in expected direction as both distance and elevation have a significant and negative effect on route frequencies. The results are consistent with previous studies; routes that are strenuous will in most cases have lower ridership levels (Mateo-Babiano et.al, 2016; Fishman et.al, 2013). For example, for every 1km increase in route distance, a route's expected log count decreases by -.793. Furthermore the results demonstrate that a 10m increase in elevation difference between start station and end station negatively effect route frequencies. The results exemplify what already has been argued; spatial constraints limit bikesharing usage. When capability constraints become too large other transportation modes than bikesharing become more convenient.

From a theoretical perspective distance and elevation can be viewed as elementary in explaining route frequencies. The pseudo R^2 value for the first step tells that the variables together explain around 3.20 % of the variation in the dependent variable. Why some routes are frequently cycled compared to others is therefore mainly explained by other factors than the distance and elevation.

5.2.3 Step II- The effect of urban form characteristics at origin/destination

In the second step urban form variables and station locks are added to the model and the results show that all new coefficient estimates are highly significant at a 99.9% confidence level. The pseudo R^2 statistics have a small increase, signifying that urban form and station locks are contributing to explaining route frequencies (Field, 2018).

Recalling chapter 3 the urban form characteristics at origin and destination stations are a result of the 250m buffers around each station, taking on the value of any grid cell intersecting the buffer, informing about local neighbourhoods at the bikesharing stations. The urban form coefficients demonstrate that the built environment is associated with higher expected log counts on the dependent variable. Because many of the coefficients are measured on different scales however the comparison is somewhat challenging. Population density is for example measured by an increase of a 1000 people, whereas building use diversity is based on an index. With that said a more direct interpretation can be conducted for the respective urban form coefficients at origin and destination station of the route. Table 5.1 shows that there are few and marginal differences between the effect of urban form at origin- and destination- station of the route. The maps presented in the descriptive section of the results chapter suggested for instance that there would be more differences between the urban form characteristics at origin and destination of the routes. One small, but noteworthy difference that can be read from the coefficients in table 5.1, is that having a diverse building diversity at the destination station of a route is associated with routes that have a higher expected log count.

Number of station locks was also added to the model. The results are consistent with previous findings and not surprisingly the results show an association between having more locks at the station and higher expected route frequencies, since the number of locks enable more frequent use (Noland et.al 2016; El-Assi et.al., 2015).

By adding urban form and station locks to the model the coefficient values and z-scores of distance and elevation have been reduced. The reduction in the variables' strength indicates that some of the effect of distance and elevation is actually explained by urban form and the number of locks at the stations. The results are in line with previous literature as they indicate that urban form facilitates sustainable transportation like cycling (Zhang et.al., 2017; Næss, 2012).

5.2.4 Step III – The effect of connectivity to metro/railway

The results from the third step indicate that integration between bikesharing and metro/railway is taking place in Oslo. This is suggested by the positive coefficient values and significant z-scores for trips that are only connected to metro/railway at one end of the route as the expected log count for such routes are higher than unconnected routes. Moreover routes that are connected to metro/railway at both ends are not significantly different from unconnected routes.

The results suggest that bikesharing is used to access and/or egress metro and railway stations, a finding that is in line with previous studies (Noland et.al., 2016; Yang et.al., 2012; Lansell 2011; Ma et.al., 2018). The result is indicated by higher expected route counts for connected routes compared to unconnected routes. Interestingly, routes that are connected are origin station have a relatively high expected log count of .329 compared to routes that are not connected. The expected increase in log count for routes that are connected to a metro/railway at the destination station is marginally lower at .255. The result from the model thus indicate that bikesharing might be especially important for egress trips.

In line with the hypothesis, the results indicate that bikesharing is used for intermodal travel. With that said intermodal travel may not happen to a substantial degree even though the urban environment facilitates such travel. There is a possibility that the results are a consequence of other urban phenomena taking place in areas that have a metro/railway station. Controlling for the effect of urban form characteristics around bikesharing stations as well as route characteristics has therefore been of especial importance because metro and railway stations are often located centrally (Sung & Oh, 2011). This tendency is for instance exemplified by the reduction in the effect of building use diversity when adding the variable measuring metro/railway connectivity, an indication that some of the effect of diversity was actually a result of connectivity to metro/railway stations. Furthermore since there are urban factors taking place around metro and railway stations that impact increased route frequencies, I would have expected that connectivity at both ends of a route would be positively and significantly different from unconnected routes. Thus the results indicate that intermodal travel is happening.

The small increase in the pseudo R^2 signifies that connectivity to metro/railway is only marginally explaining route frequencies in its whole. Explaining travel behaviour is complicated and the aim of the analysis has not been to explain the whole variation in the dependent variable, but rather see whether there is a relation between bikesharing route frequency and connectivity to a metro/railway station.

Table 5.1:Results from NBR models with bikesharing route frequencies as dependent variable

	Step I		Step II		Step III	
General frequency						
Route characteristic	Coef.	Z-score	Coef.	Z-score	Coef.	Z-score
Route distance (in km)	-.742	-132.04***	-.664	-100.29***	-.667	-100.38***
Elevation (in 10m)	-.075	-28.51***	-.073	-23.78***	-.072	-23.61***
Station characteristics						
Locks at start station			.025	26.76***	.026	27.97***
Population density at start station			.021	11.23***	.023	12.53***
Building use diversity at start station			.399	10.85***	.343	9.27***
Centrality at start station			.006	10.63***	.006	9.86***
Locks at end station			.025	27.00***	.026	27.78***
Population density at end station			.023	12.52***	.025	13.15***
Building use diversity at end station			.435	11.74***	.391	10.48***
Centrality at end station			.006	10.66***	.006	10.33***
Metro/railway connectivity						
Routes with metro/rail connectivity <200m from end station					.255	7.89***
Routes with metro/rail connectivity <200m from start station					.329	10.10***
Routes connected to metro/rail at start- & end- station					.046	.53
Ref: routes with no connectivity to metro/rail					0	-
R^2	.0320		.0383		.0387	

p<0.001***, p<0.01**, p< 0.05 *

5.3 THE EFFECT OF PUBLIC TRANSPORTATION CONNECTIVITY ON MORNING- AND AFTERNOON-ROUTE FREQUENCIES

5.3.1 Step I - The effect of route characteristics

The results from Table 5.2 show that distance and elevation is negatively impacting morning and afternoon route frequencies. Both the pseudo R^2 values in the table are higher than the previous model, which only looked at bikesharing frequencies in general. This indicates that time of day is also important for explaining route frequencies. An interesting finding is that distance and elevation have a larger negative effect on expected route count for morning frequencies compared to afternoon frequencies. This is especially the case for elevation, demonstrated by the coefficient value. For every 10m elevation difference between origin and destination station the expected log count is reduced by -.15. The effect of elevation is noteworthy lower for afternoon route frequencies as a 10m increase in elevation is expected to reduce the log count by -.029. This result is in line with previous literature which finds an effect of hills on bikesharing user frequencies (Liu et.al. 2012).

Since urban form is not controlled for the travel pattern could also be a result of Oslo's urban form and topography as residential areas are typically found at a higher altitude than that of the city centre, which is closer to sea level (Kartverket 2017 & SSB, 2017). The strong effect of elevation may therefore rather be a result of the commuter travel pattern illustrated in map in Figure 5.1.

5.3.2 Step II - The effect of urban form characteristics at origin and destination station

The results from the second step demonstrates that the effect of urban form characteristics at the bikesharing stations vary considerably between the morning and afternoon as suggested in the maps in Figure 5.1 and 5.2. All variables are significant at the 99% level or higher, and unlike the results from the model above some of the urban form coefficient values are negative.

The urban form coefficients for morning route frequencies show a clear tendency to go from residential area towards the city centre as indicated by the maps in Figure 5.1. Centrality at origin station for morning trips are for instance negative, whereas population density linked to residential areas, is relatively speaking strongly influencing route frequencies. Population density at destination station, on the other hand, is negatively associated with higher route frequencies. Routes ending in central areas have contrariwise a positive impact on the dependent variable. The coefficient of building use diversity is positive on both origin and destination, but routes that end at a station with high building use diversity is associated with higher route frequencies, a travel pattern which is consistent with previous studies on urban form and transportation behaviour (Ewing & Cervero, 2010).

Urban form seems to be less decisive during the afternoon as all the respective coefficient values are positive. Centrality and building use diversity at origin station is however associated with higher route frequencies than centrality and building use diversity at destination station. Furthermore population density at origin station indicate that for every thousandth person in the area the routes log count is expected to increase by .004. In comparison population density at the routes' destination station is associated with an expected log count of .030, suggesting that routes going from the city centre to residential areas are associated with a stronger effect on route frequencies during the afternoon. The results however strongly suggest that the mobility pattern during the morning has a more distinct direction from residential area to central areas and areas with high building use diversity. As previously argued this may be due to more time-geographic constraints during the morning hours. All urban form variables are for instance positively effecting afternoon route frequencies showing a more varied mobility pattern.

By adding the new variables the effect of distance and elevation has been reduced for both models. This is especially the case for the strong negative effect elevation has on morning route frequencies. By controlling for urban form the expected log count is -.101 for every 10m elevation difference between start- and end- station compared to -.150 in the first step. Interestingly the effect of elevation become stronger for afternoon routes after controlling for urban form. Distance on the other hand has a weaker association with afternoon route frequency when controlling for urban form. The pseudo R^2 values increase for both models. The effect of urban form and station locks seem to be especially important for the explanatory power for morning frequencies as the R^2 value increases from .0446 to .0668, compared to the R^2 for afternoon route frequencies which changes from .0454 to .0536, further suggesting that time geographic constraints are more apparent during the weekday morning peak.

5.3.3 Step III - The effect of connectivity to metro/railway

The variable measuring connectivity to metro/railway is added to the model and the results are similar to those presented in Table 5.1. Only looking at commuter hours has increased the models' overall explanatory power indicated by the slightly higher pseudo R^2 values.

By looking at commuter hours the model demonstrates that the effect of connectivity is stronger during the morning than the afternoon, being in line with the hypothesis. This is especially the case for trips that are connected to metro/railway at origin station, suggesting that bikesharing is playing an especially important role in weekday egress trips between 06am and 08am. The expected increase in a routes' log count is .468 compared to routes that are not connected to metro/railway stations. As the descriptive results in Figure 5.6 indicate there is also a significant association between access trips to the metro/railway system and increased morning route frequencies. Being connected with the metro and railway system at the destination station has however a lower effect on route frequencies. Being connected to both ends of a route has the same result as found in the previous model, as the effect is not significantly different from being unconnected.

The same association is found for connectivity on afternoon route frequencies, the effect is however somewhat smaller. Connectivity at origin station is also here in relation to the other connectivity variations strong, demonstrated by the coefficient value of .316, compared to connectivity at destination station which has an expected log count of .237 larger than routes that are not connected to a metro/railway station. This result is opposite to the hypothesis, as access and egress trips was expected to vary during the day.

By adding the new variables there are few changes in the controls for morning- and afternoon - route frequencies, with the exception of building use diversity. It is interestingly the building use diversity at origin station for both models which has the largest change in the coefficient value. This may be explained by the location of metro and railway stations, which are often placed in key locations within the city (Sung & Oh, 2011). By adding the variable *connectivity to metro/railway*, it demonstrates the relative importance of these transportation modes on generating trips.

Table 5.2: Results from NBR models with bikesharing weekday morning and weekday afternoon route frequencies as dependent variable

	Step I		Step II		Step III	
Weekday morning peak route frequency (6:00-9:00)						
Route characteristic	Coef.	Z-score	Coef.	Z-score	Coef.	Z-score
Route distance (1km)	-.793	-90.72***	-.714	-76.78***	-.713	-76.45***
Elevation (10m)	-.150	-45.21***	-.101	-27.40***	-.101	-27.31***
Station characteristics						
Locks at start station			.015	12.70***	.017	14.22***
Population density at start station			.058	24.69***	.063	26.41***
Building use diversity at start station			.742	16.28***	.687	15.14***
Centrality at start station			-.002	-2.82**	-.003	-4.00***
Locks at end station			.026	22.40***	.027	23.00***
Population density at end station			-.023	-10.42***	-.022	-9.89***
Building use diversity at end station			1.060	22.53***	1.012	21.20***
Centrality at end station			.008	10.82***	.008	11.43***
Metro/railway connectivity						
Routes with metro/rail connectivity <200m from end station					.269	7.23***
Routes with metro/rail connectivity <200m from start station					.464	11.84***
Routes with metro/rail at start and end station					-.171	-1.64
Ref: routes with no connectivity to metro/rail					0	
R^2		.0446		.0668		.0680
Weekday afternoon peak route frequency (15:00-18:00)						
Route characteristic						
Route distance (1km)	-.707	-113.14***	-.646	-91.66***	-.651	-91.90***
Elevation (10m)	-.029	-11.61***	-.045	-15.03***	-.044	-14.95***
Station characteristics						
Locks at start station			.020	22.23***	.022	23.58***
Population density at start station			.004	2.38**	.006	3.66***
Building use diversity at start station			.350	9.80***	.289	8.02***
Centrality at start station			.006	11.57***	.006	11.15***
Locks at end station			.017	18.95***	.018	19.85***
Population density at end station			.030	17.16***	.032	17.84***
Building use diversity at end station			.295	8.25***	.260	7.27***
Centrality at end station			.004	8.21***	.004	7.73***
Metro/railway connectivity (<200m)						
Routes with metro/rail connectivity at end station					.237	7.80***
Routes with metro/rail connectivity at start station					.316	10.36***
Routes with metro/rail at start- and end- station					.090	.274
Ref: routes with no connectivity to metro/rail						
R^2		.0454		.0536		.0544

$p<0.001$***, $p<0.01$**, $p< 0.05$ *

5.4 CONCLUDING DISCUSSION

In this chapter the results from analysis regarding bikesharing route frequencies have been presented, with especial emphasis on how this is related to connectivity to metro/railway stations. The main results from the chapter suggest that integration to metro/railway stations is an important function of the Oslo city bike, a finding that is consistent with results from other cities like Beijing, Shanghai and Melbourne (Yang et.al, 2010; Lansell, 2011). The results demonstrate that routes that are connected to a metro or railway station at one end of the route have higher expected log counts than unconnected trips, suggesting that bikesharing is used for access and egress trips from metro/railway stations. All models suggest that egress trips are important for higher route frequencies and this trend is especially apparent during the morning commute.

Metro and railway stations differ from other public transportation modes in that the stations are placed further apart, are separated from other traffic, in addition to connecting larger areas to the city centre in an efficient manner (Opheim et.al., 2018). Because of the relatively long distance between the stations access to certain areas in the city can be low when travelling by rail, and the results strongly suggest that bikesharing plays an important role in covering the last mile for metro- and railway- trips. Bikesharing can therefore be increasing the accessibility for certain areas in Oslo where the distance between metro/railway station and final destination is not too far and strenuous, thus lifting individuals' time-space constraints.

Research on bikesharing from other cities show that urban form impacts ridership patterns and the results from the analysis show that the same trend is apparent in Oslo (Liu et.al. 2012; Zhang et.al., 2016). Population density, land use diversity, destination accessibility and access to public transportation are all positively impacting daily route frequencies and urban form at origin and destination station have a similar effect. The results do however vary when looking at morning- and afternoon - frequencies, where especially morning frequencies show that urban form at origin and destination station has a higher impact on route frequencies. The result demonstrates a typical commuter pattern starting in highly populated residential areas and ending in central and diverse areas during the morning. Conversely afternoon route frequencies are associated with a central and diverse urban form at origin station and end in areas with higher population density. With that said the afternoon mobility pattern shows higher degrees of variety, illustrating how time and urban form are enabling and constraining certain travel behaviour.

Comparing the descriptive results to the models' results the analysis shows the importance of controlling for the effect of urban form in order to know whether it is connectivity to metro/railway stations that is impacting route frequencies or if the effect is spurious, originating from other urban aspects. The descriptive results presented in Figure 5.5 indicate for instance a relatively higher importance for access trips compared to egress trips. The question is then if important urban characteristics have been exempted from the models. As only connectivity to one end of the route is affecting route frequencies there are few indications that there is something about the urban characteristics around metro and railway stations that is the underlying cause of the results.

From a time geographic perspective, the results indicate that time imposes limitations. Morning trips are less varied, starting and ending at similar locations, a result of an aggregated commuter pattern. The relatively strong and negative association between distance and elevation on morning route frequencies, compared to afternoon and general route frequencies, indicate that there are more time geographic constraints during the morning hours. Afternoons on the other hand are linked to varied mobility patterns, as bikesharing is not only used for commutes, but also for more recreational purposes. This is suggested by start and end stations being to a higher degree the same. Moreover the negative impact of distance and elevation is weaker during the afternoon.

6 CONCLUSION AND DISCUSSION

Climate change has called for broad social, economic and technological transformations and optimism towards sharing as a solution has been apparent, especially in the transportation sector, as transportation is responsible for a large share of total greenhouse gas emissions (Moss, 2015). It is argued that by utilising transportation modes more efficiently, some of its negative externalities like congestion and air pollution may be reduced (Shaheen, 2016). Shared mobility has therefore been advocated by many city governments and obtaining a bikesharing program has been a desirable transportation policy. However to what degree bikesharing can contribute to sustainable travel is debated as the majority of bikesharing trips are replacing other sustainable transportation modes, something that has made its critiques argue that the benefits of bikesharing are exaggerated (Fishman et.al. 2013). In combination with public transportation it is however agreed upon that bikesharing can play an important role in serving as a feeder mode for the first and last mile of a transportation journey, making public transportation more efficient and attractive in its whole.

Similar development has occurred in Oslo. The Oslo City Bike was advocated by city officials and the programme is visibly promoting Oslo as a green city (Alsvik, 2009). Its role as a sustainable transportation mode has however been unclear and was an area in need of research. Especially so because of ongoing Mobility as a Service development aiming at combining public transportation and shared mobility services (Aarhaug, 2017). As transportation is showing signs of moving from being ownership based to service based it has been especially important to study intermodal travel and how conventional transportation modes, like public transportation and shared mobility are being used and potentially integrated in people's everyday mobility pattern.

The thesis has sought to address three knowledge gaps in previous literature on bikesharing integration with public transportation. Firstly, previous research has tended to study members and non-members of bikesharing systems separately (Guo et.al., 2017; Bechand-Marleau & El-Geneidy, 2012; Efthymiou et.al 2013). By viewing these two groups together it has been possible to identify key differences in access to and use of public transportation that might play an important part in not only stating to be interested in participating in bikesharing, but taking an actual step to become a member. Secondly, previous literature has tended to have a limited focus on modal integration. An extended definition of integration has been beneficial in order to see bikesharing in the context of daily mobility as the narrower definition has partially resulted in a knowledge gap in this area. This has been important because public transportation might not only affect integration of bikesharing on a trip level, but also in day to day life. Finally, sample data as well as population data on station frequencies have tended to be the cases used in previous studies. From a geographic perspective, however, it is proven to be beneficial to use population data on routes as cases. By studying bikesharing routes it has been possible to identify the effect of urban form and connectivity at origin and destination of a route seeing this in relation to each other.

6.1 RESULTS

The main research question of this thesis has been:

In what way and why is bikesharing being integrated with public transportation?

The aim of the main RQ has been to approach integration between bikesharing and public transportation in a comprehensive manner; in daily mobility as part of people's daily mobility mix and on trip levels in the form of access and egress trips to/from public transportation. This has been done by unpacking the main research question into RQ1, dealing with integration in daily mobility in Oslo and Bærum and RQ2, dealing with intermodal integration on a trip level in Oslo.

The first analysis of the thesis sought to answer RQ1:

How do daily- access and use of public transportation affect revealed bikesharing membership choice compared to stated interest in bikesharing participation?

The analysis enabled comparison between the significant variables for stating interest in relation to those of revealed membership choice. This has been important in explaining aspects which are significant for being interested as opposed to the factors that may cause people to take the actual step of becoming a member.

The aim of the analysis was to see whether bikesharing has a potential to be integrated in people's everyday transportation mix. The results found that owning a bike, combining cycling and public transportation in daily mobility as well as being a frequent public transportation user significantly affected stated interest in bikesharing participation. With that said, none of the urban form variables was associated with stated interest in participating in bikesharing, nor was having access to a car. Stated interest was however to a larger degree explained by being environmentally conscious. The results therefore suggests that stated interest is mostly a reflection of environmental attitudes rather than actual intention to join a bikesharing programme.

Interestingly, revealed membership choice was associated with aspects regarding transportation resources and urban form. Not having access to a car was significantly affecting bikesharing membership, as well as living in denser areas with accessibility to public transportation. Furthermore, the results show that combined usage of cycling and public transportation had an especially high association with membership. Contrary to stating interest in bikesharing participation, the results from the membership group indicated that having an environmentally friendly attitude is less important in explaining revealed membership choice.

The results from the analysis indicate that access to and use of public transportation is associated with bikesharing interest and membership to varying degrees. Public transportation users seem for example to state higher interest levels; in addition access to public transportation is linked to membership. Integration in daily mobility is indicated by the results showing a clear association between combining cycling and public transportation in the daily mobility of bikesharing members. Thus integration between the transportation modes on a daily basis seem to be occurring in Oslo and Bærum. This might be related to opportunities and constraints linked to living in urban areas without access to a car. Bikesharing, along with other transportation modes, might be beneficial in overcoming certain spatio-temporal constraints for these individuals.

The results linked to RQ 1 are in line with Lanzini & Khan's (2017) findings on transportation behaviour; most people fail to act according to pro-environmental beliefs. The results suggest that bikesharing may be related to sustainable beliefs, but it does not result in membership. The analysis indicated that bikesharing membership is relevant as long as it is a sufficiently convenient transportation mode, suggested by the significant urban form- and no car access-coefficients for revealed membership choice. Walking the talk is therefore unlikely, regardless of stating interest in participation as long as the transportation mode is not sufficiently convenient.

The second part of the analysis aimed at seeing to what degree bikesharing and public transportation is being integrated in individual journeys by answering RQ2:

What impact has connectivity to public transportation, along with other urban form aspects at bikesharing origin and destination stations, on bikesharing route frequencies?

The connectivity between bikesharing stations and metro/railway stations was explored because of the methodological implications related to including the whole public transportation system in Oslo into the analysis. The urban form characteristics in the areas of bikesharing origin and destination station (density, diversity and destination accessibility) and route characteristics (distance and elevation) were controlled for in order to isolate the effect of connectivity on route frequencies. The results from the analysis showed that bikesharing routes with connectivity to a metro/railway station at one end of the route are associated with increased route frequencies. The finding suggests that bikesharing is being used for access and egress trips to or from metro and railway stations. An interesting result is that bikesharing stations connected to the metro- and railway- system at origin station are associated with higher user frequencies regardless of time of day. This finding suggests that bikesharing might be playing an important role in covering the last mile of metro and railway journeys.

Furthermore the results demonstrate variation in spatio-temporal attributes, since the effect of urban from, elevation and connectivity varies during morning and afternoon. Routes during the morning peak show for instance a clear mobility pattern from residential areas towards the city centre. Morning routes that are connected to a metro or railway station at the origin station are associated with especially high route frequencies, indicating that bikesharing may have an important integrational function with the metro and railway system. The afternoon peak is on the other hand related to more varied trips, and connectivity in comparison to morning routes is less important during the afternoon. This may be linked to different spatio-temporal constraints through the day.

The results from the analysis presented in this thesis can together answer the main RQ. All models in the thesis suggest that public transportation and bikesharing is being combined in everyday life as well as on individual journeys. Two key findings on how bikesharing is being integrated is worth noting. Firstly, the analysis indicates that being reliant on multiple sources of transportation is linked to bikesharing. People who have a habit of combining public transportation and cycling are for instance more likely to state to be interested in bikesharing, as well as subscribing to a bikesharing scheme. Having a broader mix of publicly available transportation modes might therefore be explaining why bikesharing is integrated in daily mobility.

Secondly, on an individual trip level the results from the analysis show that bikesharing might be especially important in covering the last mile of longer metro/railway journeys, in form of egress trips. This finding suggests that people are travelling from Oslo's suburbs and surrounding municipalities to the city by metro/railway and the last mile of the journey is covered by bikesharing. Using the system to access the metro/railway system is however not happening as frequently. The flexibility and convenience bikesharing can offer in terms of one-way trips seem to be important for integration on an individual trip level and function as a supplement to other transportation resources.

6.2 LIMITATIONS

There are a few limitations with this thesis which need to be addressed. Firstly, despite significant results the importance of integration with public transportation should however not be exaggerated, as the pseudo R^2 values of the analysis indicate that a large degree of the variance in the dependent variable remains unexplained in my models. This has especially been the case for the route frequency models on access/egress. Other factors that were not included in the analysis clearly play a considerable role in explaining stated membership interest, revealed membership choice and route frequencies. This highlights the fact that the models are not only a result of the variables I chose, but also the fact that they are based on a theoretical framework that mainly seek to explain travel behaviour through quantifiable urban and social characteristics. The variables in the models thus attempt to quantify complex and sometimes intangible concepts such as mobility patterns, urban form, attitudes and gender, and to what degree this can be achieved through chosen method is debated (Cresswell, 2013). Low pseudo R^2 values are however common in transportation studies, an indication that transportation behaviour is highly complex and difficult to model (Ferrer & Ruiz, 2013).

The second limitation is linked to the representativeness of the sample used to answer RQ1. In chapter 3 where the representativeness of the sample was discussed, the composition of the sample compared to the population of Oslo and Bærum was similar in many aspects. With that said, compared to previous studies socio-economic characteristics have played a much smaller role in Oslo and Bærum (Fishman et.al. 2013). Whether this is a result of sample skewness, inaccurate operationalisation or a reflection of being a Northern European welfare state is however uncertain.

A third limitation is concerned with the assumption that combined travel is likely when the distance between public transportation and bikesharing is short. Many trips taken at bikesharing stations close to public transportation are probably not intermodal. They could be the cause of some other facility close by the bikesharing stations. This shortcoming has been accounted for by controlling for urban characteristics such as population density, building use diversity and centrality at the bikesharing stations, important factors may however have been left out from the equation. With that said the consistency of the result compared to other literature suggests that proximity is important for intermodal travel (Noland et.al. 2015).

Finally, some caution should be taken when viewing the individual effect of the independent variables as some of them may have a collinear relationship (Field, 2018). This may be the case of variables concerning urban form and attitudes which are known to be highly related to one another. Extreme collinearity has however been accounted for verified by statistical testing. In addition it has been necessary to raise the question of the actual independence of the independent variables in the analysis. This is especially the case for analysis regarding route frequencies as the location of bikesharing stations may have been chosen with the goal of increasing route frequencies in mind, making the direction and effect a fuzzy concept to model.

With that said, even with these limitations the thesis should have sufficient validity. The results in the thesis has been consistent with earlier findings, an indication that there are no major flaws with the variables and modelling techniques that have been applied. Furthermore, the results from the different models have been complementary of each other and the overall logical results of the thesis further suggest valid results.

6.3 THEORETICAL IMPLICATIONS

There are four main theoretical contributions from this thesis. Firstly, results from this thesis suggests that stated interest towards certain transportation modes might rather be a reflection of general attitudes than an actual intention of changing transportation behaviour. It might therefore be more fruitful to look to past behaviour for explaining transportation choices, as walking the talk has proven difficult in many occasions (Lanzini & Khan, 2017). Furthermore the thesis has shown that spatial attributes seem to play a smaller part in explaining intangible concepts such as interest. Consistently with previous literature on the topic, spatial attributes also in a Northern European context, are important in explaining bikesharing related behaviour (El-Assi et.al., 2017; Campbell & Brakewood, 2017).

Secondly, the analysis suggests that skills and habits are important in explaining interest in bikesharing as well as becoming a member. Bikesharing is likely highly reliant on cycling skills and confidence, which goes hand in hand with owning a bike. What is more, results from the thesis have indicated that bikesharing is being used as a supplement to the privately owned bike. The pro-environmental behaviour of bikesharing might not be a result of individuals' attitudes, but rather a result of routine (Hargraves, 2011). The theoretical approach to bikesharing might therefore benefit from social practice theory. Furthermore do the results suggest that the discussion on bikesharing substitution and integration should also include bikesharing's potential to supplement public transportation modes.

Thirdly, findings from this thesis strongly suggest that studying bikesharing on a route level has been beneficial for understanding its role in access- and egress- trips. As bikesharing can serve an important role in covering the first and last mile of public transportation journeys it is important to assess and compare its role in different cities to gain a further understanding of the role bikesharing plays in access/egress trips. Currently analyses are conducted in multiple ways, making comparison between cities difficult. The route-analysis used to answer RQ2 can however be universally replicated and used to cross compare cities. Measuring urban form characteristics at bikesharing station using ratios and indexes might be especially beneficial for this purpose.

Finally, having a time geographic approach has proven beneficial in understanding mobility patterns, both in daily life as well as on individual trips. Access to transportation resources can lift the time-space constraints, consequentially increasing individuals' time space prisms. To what degree bikesharing can sufficiently contribute to increasing individuals' spatial reach is however related to opportunities and constraints of individual characteristics, urban form and existing transportation resources. Furthermore time geography has been helpful in understanding spatio-temporal variations throughout a day. Applying a time geographic perspective to understand bikesharing commuter patterns has for instance been an advantage.

6.4 POLICY IMPLICATIONS

The results from this thesis can be relevant for policy in a number of ways. Firstly, results have pointed to convenience being important for sustainable travel. This finding suggests that awareness campaigns promoting sustainable travel will in many cases not be sufficient in reaching this goal. This study indicates that acting according to environmental beliefs is reliant on facilities and infrastructure which makes choosing sustainable transportation convenient and easy. Facilitating for sustainable travel in areas where people live as well as at transportation hubs may therefore be especially important in reducing petroleum related greenhouse gas emissions in cities.

Secondly, results from this thesis has for instance found that respondents who have access- to and use- multiple transportation modes are more likely to be interested in bikesharing as well as being a member. Developments like Mobility as a Service can serve an important role in making combined travel easier, by integrating different types of transportation modes within a single app as well as universal ticketing. Findings from this thesis however, strongly suggest that this alone is not enough; intermodal travel with public transportation and bikesharing is reliant on the physical environment. Integrated travel solutions in smartphone apps therefore need to go hand in hand with physical development in cities, in order to properly facilitate for sustainable mobility.

Finally, the analysis from this thesis indicates that bikesharing is playing an important function in covering the last mile of metro- and railway- journeys in Oslo. Facilitating for bikesharing at metro- and railway- stations might therefore be beneficial for both transportation modes- as bikesharing can increase the reach of the public transportation service in its whole by covering the first and last mile. It might therefore be important to integrate bikesharing in the future development of metro- and railway- stations.

6.5 FUTURE RESEARCH

There are a number of topics that I have not been able to answer in this thesis which require further investigation. Firstly, even though the results from RQ1 indicated small effects of gender on bikesharing membership in Oslo and Bærum, gender is consistently associated with bikesharing membership through previous literature (e.g Liu et.al., 2012, Adams et.al., 2017; Fishman et.al., 2013). Further research should therefore address the issue of the inclusiveness of bikesharing systems. This might be especially interesting in a Northern European context as countries in this region are known for limited inequalities in many areas (Dickens, 2014). Secondly, results from chapter 4 suggested that bikesharing might be related to early adopters, and further understanding bikesharing interest and membership in terms of early adopter literature can be fruitful in research of the topic (Shaheen, Martin & Guzman, 2011).

Thirdly, this thesis viewed bikesharing membership in relation to individual characteristics, urban form and public transportation. The next step to gain further knowledge on bikesharing can be to study motivations for recruitment as well as causes for unsubscription from bikesharing schemes. Fourthly, it has been argued that stated interest in bikesharing rather is a reflection of a general attitude towards green transportation modes than an actual intention to subscribe to a bikesharing scheme. If this is the case, interest as a measure for transportation planning is flawed and can have theoretical and practical implications. A longitudinal study exploring whether interest in bikesharing is related to membership at a later point in time therefore is important' and is a topic in need of research.

Fifthly, RQ2 builds on two assumptions; that proximity between bikesharing and public transportation facilitates intermodal travel and that people tend to choose shorter routes. Addressing these assumptions is important in future studies of bikesharing. This can be done in a number of ways, both quantitatively and qualitatively, for instance by asking directly about multimodal travel in surveys, or GPS tracked multimodality. Finally, bikesharing is usually approached quantitatively (Fishman et.al., 2013), but in-depth interviews with members as well as non-members can be beneficial for further understanding of this rapidly expanding transportation mode.

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Appendix

Sources of map layers

Data	Source	year	Projection	Description
Statistics on grid cells	SSB	2017	GCS_WGS_1984	Grid cell on 250x250m. Statistics on population and building mass
Open street map	geofabrikk.dk		NA	Network data
NSB GTFS	Entur	2016	GCS_WGS_1984	Point data on railway stops
Ruter GTFS	Entur	2017	GCS_WGS_1984	Point data on public transportation stops
Bikesharinging trip data	UIP	2017	GCS_WGS_1984	Population data on bikesharing trips from 2016-2017
Digital terrain model	Kartverket	2013	GCS_WGS_1984	Grid cell data on 10x10 m informing about altitude
Basis data FBK	Kartverket	2017	GCS_WGS_1984	Data on geographical features such as sea, water and parks