ERASMUS UNIVERSITY ROTTERDAM

ERASMUS SCHOOL OF ECONOMICS

MSc Econometrics and Management Science

Master Specialisation: Quantitative Marketing

Incorporating Spatial Dependencies in a Multinomial Logit Model:

A Company Level Analysis for Transportation Choice in Belgium

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Finish date: [09 2013]

PREFACE AND ACKNOWLEDGEMENTS

I would like to thank my supervisor, Prof. Dr. Peter Goos, for his guidance and support in my efforts for the completion of this dissertation. I would also like to give my thanks to Dr. Thomas Vanoutrive for sharing his knowledge on the subject.

Moreover, I would like to express my deepest appreciation to Prof. Dr Oliver Kuss for his precious help and suggestions and also to express my gratitude to all the authors who contributed to enrich my knowledge and therefore to the accomplishment of this study.

Finally, I would like to deeply thank Natasa Gassia and Pinelopi Christoforatou for their presence and support in difficult times and also Allina Koutsoura for her help and interest.

Last but not least I would like to express my acknowledgement to my family for always being there.

ABSTRACT

In this thesis, commuter's transportation choices for their Home-To-Work travel (HTWT) are analyzed with respect to the companies' characteristics in Belgium. The main focus is on mobility management measures, which are mobility policies whose main aim is a sustainable transport system, as well as external factors related with municipality characteristics and the infrastructure of the area. Taking into account spatial autocorrelation, which is referred to the dependency among companies over space, a mixed multinomial logit model involving random effects was considered.

The results show that 'Guaranteed ride home' and 'Organization of carpooling' are efficient mobility management measures for promoting carpooling. In addition, fixed work schedules increase carpool use compared with car use. On the contrary, flexible work schedules contribute more to increase metro-tram-bus and train usage. Also, the existence of bus and train stations nearby the company is a major factor for employees to choose public transportation for their HTMT. Finally, regarding mobility management measures, financial incentives motivate more commuters to travel by bicycle instead of by car. However, external factors also have a large impact on commuter's behavior regarding cycling. In particular, the slope of the road network and job density are negatively related with cycling. The random effects in our model show that there are some unobserved factors that differ among boroughs which have an impact on employees' choices regarding train usage.

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1. INTRODUCTION

Traffic congestion is one of the most unpleasant and difficult situations that large cities are confronted with. Specifically, in urban cities, where a lot of companies and industries are located, the congestion is growing. Such areas are more attractive to people, as there are more opportunities in several fields resulting in increasing their population. However, traffic jam negatively affects human well being and citizens' quality of life due to noise and stress and also due to the greater possibility of accidents. Moreover, there are environmental impacts, as wasted fuel, air pollution and carbon dioxide emissions. Finally, traffic jams influence the economic health and causes considerable costs due to non-productive movements and substantial waste of time. In essence, traffic congestion occurs when the 'size' of traffic engenders higher demand of space than the available capacity. According to this, there are two ways to decrease the negative effects that were mentioned above. The first way concerns the increase of capacity (supply) while the other concerns the reduction of demand and the encouragement of the use of alternative means of transportation which are friendlier to the environment and also prevent congestion.

There are two kinds of congestion. The first one is referred to as "non-recurrent congestion" and it is the result of unpredicted events (e.g. road works, accidents) or specific circumstances like bad weather conditions[1]. However, these facets have not received great research attention as they cannot be easily estimated. The second type of congestion is referred as "recurrent congestion" and it is the consequence of factors that act regularly or periodically on the transportation system, such as daily commuting which is essentially the "Home to Work Travel" (HTWT). However, the daily commuting to work is closely connected with the company the commuter works for and its properties (e.g. location, mobility management measures etc.). As it is mentioned above policies based on demand management seem to be vital in order to reduce the negative outcome of transport. Such approach is called 'Mobility Management' and it seeks to give a solution in congestion-related difficulties via various tools and strategies. Mobility management measures are policies which are implemented by employers in order to contribute to mobility management. This study seeks to analyze employees' choices for the HMWT with respect to companies' characteristics.

[1] Source of Transportation Cost and Benefit Analysis II- Congestion Costs- Victoria Transport Policy Institute (www.vtpi.org)

A commuter can choose among various means of transport in order to reach his/her work. They sometimes walk or they use their bicycle, motorcycle, car or even carpooling. Carpooling or alternatively car-sharing is the sharing of car journeys when two or more commuters use a car. Note that carpooling is one of the alternative modes promoted by transport policies, in order to reduce traffic congestion (Vanoutrive et al., 2011). Another portion of commuters use public transportation like bus, metro, tram or train.

However, the mode choice depends on the distance that should be crossed and also on the travel time required by each mode (Van Wee et al. 2006). Moreover, some characteristics of the companies play a key role in employees' decisions regarding the 'Home to Work Travel'. Such features are related to the location of the workplace (Rietveld and Daniel, 2004). For example a train or bus station nearby the worksite can influence and lead a commuter to use the respective mode. Another factor is that of accessibility. Some workplaces or even municipalities are confronted with accessibility problems which might affect commuters' behavior.

Mobility management measures on the part of companies are also important regarding commuting behavior of their employees. Financial incentives, providing facilities and parking management play a fundamental role in mobility management (Van Malderen et al. 2011). In essence, mobility management measures are mobility policies whose main aim is to establish and improve a sustainable transport system. Several initiatives have been developed in order to achieve such a purpose. Such policies concern the promotion of alternative modes, alternative work schedules, parking policy, location strategies and the ways to simplify the operation of these measures. Incentives can be either financial or through the provision of services and facilities. So as to better understand the vital role of the mobility management measures in the current study, a further operational description of each measure follows in the second chapter.

Particularly, this study focuses on Belgium and its large companies. The available data set contains information of worksites with at least 30 employees in Belgium in 2005. Large Belgian companies are obliged by law to collect data concerning the travel mode used by their employees when commuting to work. The goal of the current thesis is to explain the mode choice as a function of the companies' properties; size, sector, location, public transportation stops nearby the company, implementation of several mobility management measures, accessibility problems or other difficulties, municipality and municipalities' characteristics. The aim is to gain knowledge and be able to make recommendations so that the transport policy makers pick the right decisions and make the required adjustments so as to weaken traffic congestion due to commuting.

The main research question in this thesis is: '*Which company and location factors affect commuters' behavior in Belgium*'. More precisely, we tackle this research objective by answering the following sub-questions:

- What are the differences in commuters' choices with respect to the sector a workplace belongs to?
- Which of the mobility management measures contribute most to a sustainable transport system?
- Which problems /difficulties contribute more to the increase of commuting-related problems and which less?
- Is mobility management finally capable to lead to a sustainable commuting?

To address these issues, we build a multinomial logit model that explains the mode choice as a function of the company properties and properties of municipalities. However, we should take into consideration the so called "spatial autocorrelation". This practically means that commuters who work in companies that are close to each other exhibit similar behavior. To account for this spatial dependency, a mixed multinomial logit model involving random effects associated with the companies' locations, is used. The random effects capture the unobserved factors, related to the location of a company, that affect employees' transportation choices.

This paper is organized as follows. Definitions of key terms and concepts, an extensive description of mobility management as well as background knowledge concerning certain factors related to commuters' behavior are provided in section 2. A description of the available data set follows in section 3 together with descriptive analysis of the available variables. In section 4 our methodological framework is presented. The results of the study follow in section 5 and in section 6 conclusions are summarized together with some discussion. Finally, in section 7 limitations encountered during our research are described.

2. LITERATURE REVIEW

2.1 Introduction

Increased mobility and the concomitant reduction of negative factors such as congestion, accidents and pollution are a common challenge for many cities. The traffic congestion is a complex problem that intensifies in urban areas due to accumulated activities. Over 60 percent of the European inhabitants live in central areas with more than 10.000 residents[2]. Citizens, in their everyday life are occupying the same space and the same infrastructure for their mobility. Therefore the simultaneous movement of such residents leads to congestion which is the main source of many problems. The 2010 Urban Mobility report, issued by the Texas Transportation Institute, mentioned that in 2009, congestion evoked urban Americans to travel 4.8 billion hours more and to consume an extra 3.9 billion gallons of fuel. Furthermore, a comparison among years was conducted and revealed that congestion costs in the 439 Americas' urban areas are increasing. Specifically, the cost of extra time and fuel due to congestion was $24 billion in 1982, $85 billion in 2000 while in 2009 it was $115 billion. In the European Union, in urban areas, congestion costs are estimated at 100 billion Euros per annum[3].

A combination of individual and collective means could be the best possible solution. However, the increase in the number of cars, combined with the lack of infrastructure in the city and chaotic building lead to high congestion during peak hours. "Home-to-Work" commuting is the major cause of traffic jam. City dwellers directly experience all the negative effects of their own mobility and might be receptive to innovative solutions towards sustainable commuting. The IBM Corporation in 2009 has executed the so called "The commuters' challenge" survey, in order to gain a deeper insight of commuters' rationale and behavior. According to this survey, in the U.S. sixty seven percent (67%) of the licensed drivers use their car and drive alone for their "Home-To-Work" travel. However, twenty percent (21%) of the respondents stated that their commuting behavior was affected by the recession. Particularly, seventeen percent (17%) use carpooling more often, twenty six percent (26%) use public transportation more frequently and nineteen percent (19%) work from home more often. Moreover, the survey indicated some of the problems caused by congestion in terms of employees'

[2] Source of European Commission http://ec.europa.eu/transport/urban/urban_mobility/urban_mobility_en.htm
[3] Source of European Commission http://ec.europa.eu/transport/urban/urban_mobility/urban_mobility_en.htm

productivity. More specifically, the study mentioned that forty four (44%) of all drivers are experiencing an increase of their stress levels and that twenty five (25%) experience an increase in rage. Moreover, sixteen percent (16%) of the drivers indicated that traffic problems harm their performance at work. This frustrating situation requires a more realistic approach which will make the car "redundant", at least for travel within the city. Therefore, an effective management and the development of alternative practices are necessary in order to diminish private car use while contributing to the increase of public transport usage or alternative modes such carpooling. The most effectual policy is when actions and attempts by commuters, governments and employers operate with common objectives and in cooperation with each other (Urban Mobility report, 2010).

Another factor that has an effect on the daily movement of people and their commuting behavior is the tax regime that is implemented in relation to the “Home-to-Work” travel. The applicable laws in a country influence car and public transport usage. Specifically, in countries such as Belgium, Luxembourg, The Netherlands, Finland, France, Denmark, and Germany a general tax relief is applied for commuting trips. On the other hand, in countries such as the UK, Austria, Greece, Ireland, Spain, Portugal, Italy and the USA commuting costs are considered as individual costs (Potter et al., 2006). Both methods hide elements that potentially have negative impact on the transport system and they indirectly cause difficulties in the daily life of residents. The study of Potter et al. (2006) concluded that in countries where traveling to work is a “tax-deductible outflow”, the number of car drivers and the trip length are increasing due to the increase of general benefits. Moreover, it is mentioned that a general tax allowance is a costly measure and therefore is not efficient enough. A more proper measure is a tax allowance which focuses on public transport commuting trips. Instead, another technique is used in countries where commuting is a non tax-deductible expense. In this case, some general tax allowances should relieve employers in order to develop policies that will affect modal split and will contribute to a sustainable transport system. Such policy could be measures and incentives that promote public transport or alternative modes such as bicycle or carpooling. A balanced combination of tax concessions between employers and employees as well as the integration of environmental intentions and objectives are vital in order to achieve an efficient approach.

2.2 Mobility Management

In order to make an effective operation of transport system while parallel targeting on cost savings and positive effects on the environment, the development of a feasible and valuable management is required. Such management concerning transportation services is called "*Mobility Management, MM*". Mobility management seeks to coordinate all the components comprised in transport network according to customers' travel needs in a way that focuses on the commuter's satisfaction, facilitation and safety (Majumdar et al., 2011). Moreover, the elaboration of alternative strategies aimed at tackling traffic congestion as well as the development of policies concerning land use seeking to enhance infrastructure, are involved in Mobility Management, (Majumdar et al., 2011). MM is becoming a common trend in global level in the public transportation sector. In 1999 a European plan was developed; the so called "European Platform on Mobility Management, EPOMM". EPOMM corresponds to a set of connections of governments in European countries that deal with Mobility Management. Its major purpose is to encourage and further expand Mobility Management in Europe through knowledge diffusion and information exchanges in order to facilitate and strengthen a sustainable transport system[4].

2.3 Mobility Management measures

Mobility management includes several measures aimed either at improving infrastructure through new tram lines, highways, bike paths or at achieving the most efficient use of offered resources. The latter can be achieved either through the dissemination of information for available trip options, provision of facilities and services or even incentives which will influence commuters' behavior. MM seeks to affect commuters to make their most inexpensive and less time-consuming choice and simultaneously the most efficient in terms of sustainable commuting.

Mobility management measures that correspond to the second category are considered "soft" measures as they do not have need of great financial cost and they are easily implemented.

The corresponding action in the United States is called "Transportation Demand Management, TDM" (Rye, 2002). TDM focuses on managing and diminishing travel

[4] Source of European Platform on Mobility Management
http://www.mobilitymanagement.org/index.phtml?Main_ID=851

demand and also manipulating commuters' behavior in a way that leads to a well-organized and more tenable transport system. Effective TDM plans are capable of reducing vehicle trips and manage to support a change in travelers' tendency. However, the most efficient and wisest TDM program seeks to achieve its purpose in cooperation with local employers.

2.3.1 Employer Transport Plans, ETP

Mobility management at employer level can be developed through measures such as the promotion of alternative modes (e.g. carpooling), the establishment of alternative work schedules or telecommuting or the provision of facilities and services (e.g. parking)[5]. Such travel plans are called "Company Travel Plans" in UK or "Sited-based Mobility Management" in Continental Europe (Rye, 2002). According to Rye (1999), the ETP (Employer Transport Plans) is a set of inducements or discouragements in some cases, which aim to engender or make more forceful the sense of social responsibility of employees, as well as, to lure employees to use more advantageous transport modes. However, the study highlighted that these measures are sometimes not applicable enough and require transformations to the company's culture. Note that the present study is elaborating at employer level and thus an extensive analysis of these measures follows.

According to Van Malderen et al. (2011), for small worksites, the promotion of bicycles is considered the most suitable measure, while greater worksites which are placed in urban centers and residential areas should motivate their employees to use more public transportation. Mentioning the promotion of alternative modes we focus on the effort of elevating the usage of cycling, carpooling or public transportation. Regarding the former, companies supply many facilities such as secured bicycle storage, bicycle repair facilities, bicycle maintenance, rain clothes, showers and changing room. Furthermore, employers provide bicycles, or they offer a cycle mileage allowance and sometimes an extra fee for professional trips in order to support and encourage cycling. Another alternative is carpooling which is considered an effective way in order to reduce traffic congestion (Vanoutrive et al., 2011). Note that carpooling contributes significantly to the increase of "Average vehicle ridership (AVR)". The AVR-value of a company is defined as "the number of employees divided by the number of motor vehicles driven by these

[5] Source of Municipal Research and Services Center of Washington, MRSC
http://www.mrsc.org/subjects/transpo/tdm.aspx

employees", (Giuliano, 1993). This practically means that, the greater the AVR-index the smaller the number of motor vehicles. The increase of AVR constitutes the main objective of the "XV Regulation" within the framework of Transportation Demand Management (TDM). In this way, employees diminish their stress level and their daily expenses[6]. Except of the personal benefits, carpooling also react positively on employers and environment. Particularly, carpooling contributes to traffic congestion decline and also helps to avoid blockage within parking spots. In that way, employers can avoid the costs of building additional parking areas. Moreover, by diminishing the number of cars, air quality can be enhanced. However, carpooling is not always convenient and the extra distance that should be travelled for the door-to-door journey may increase the travel time of the daily commuting especially for the driver. Thus, some incentives should be given by the company. Such incentives are facilities like preferential parking places for carpooling employees, or guaranteed ride home for employees that use carpooling. Moreover, employees at a worksite can have access to the carpool database and sometimes carpooling is coordinated at the workplace. Finally, initiatives that encourage public transportation for the daily commuting are the provision of information on available trip providers, the promotion of public transport for work related trips, extra fee and low-priced tickets.

On the other hand, as it was mentioned above car users constitute the highest percentage of commuters. Employers often implement policies that urge employees to use their car for the 'Home to Work Travel' as they offer company cars and fuel cards as an indication of accolade and a powerful tool in order to make them more productive. In this way, employees are not likely to use another mode to commuting even if it is enough convenient. Thus, in this case parking charge is considered a compelling and sufficient mobility management measure.

Another important factor that may influence commuting behavior is work schedules and teleworking. Alternative work schedules may be executed, such as the flexible schedule, as a result of which an employee does not have a rigid timetable and thus can avoid the peak hours. Also, teleworking is referred to the way that collaboration and work can be achieved from distance in order to avoid possible business travel. Both work schedules

[6] Source of Department of Transportation
http://www.state.nj.us/transportation/commuter/rideshare/carpool.shtm

and telecommuting manage to lessen commute time costs and stress and thus improves job satisfaction which enlarges productivity[7].

Finally, several policies are related with the implementation of the mobility management measures. Their purpose is to facilitate its operation and effectiveness. Such measures are based on collaboration with enterprises, cooperation with mobility institutions, regular consultation with local authorities and the existence of a mobility coordinator (Employee Transport Coordinator, ETC) whose role is to address commuters' needs.

2.3.2 Effectiveness of Employer Transport Plans

Several studies have been conducted concerning Employer Transport Plans (ETP) and their effectiveness in terms of reducing single-occupant-vehicles (SOV). It is known that ETP plans have an impact on the reduction of employees who choose the car as a mode of transportation for their Home-to-Work travel (Rye, 2002, 1999). Also, Rye (2002) came up with some factors which deemed crucial for the effectiveness of ETP plans in the UK. Specifically, a "supportive organizational culture" in the company is considered important. This practically means that there is workforce dedicated to travel plans. Moreover, the infrastructure of a region is equally important. The best practices cannot produce the same successful results in all areas. The public transport network plays a key role for example. However, the author concluded that ETP plans were not widely implemented and that this is an issue for Government to be concerned about. The greater part of employers considered such measures superfluous or costly. Therefore, incentives related to tax release for employers who implement such plans could be a solution (Rye, 1999).

Indeed, a later study that was conducted in Belgium (Van Malderen et al., 2011), states that finally, a sufficient number of companies have implemented an ET plan. The increased interest was due to multiple factors: difficulties encountered by employers due to parking and accessibility problems and governmental measures that support companies by means of tax release. Both workforce and companies have a positive attitude towards ETP, and particularly employees favor more concrete measures, while on the other side employers desire the least expensive. However, specifically in the suburbs, despite the existence of railway or other facilities, employees tend to use more

[7] Source of Department of Transportation
http://www.state.nj.us/transportation/commuter/rideshare/telecomm.shtm

car compared to other areas. Thus, firms placed in urban fringe should reinforce incentives in order to diminish the number of single-occupant vehicles. Parking policy seems to be an essential determinant concerning the effectiveness of such plans (Van Malderen et al., 2011).

2.3.3 Municipalities' policies and characteristics

It is often observed that the labor market is concentrated in areas quite remote from residential areas (Boussauw et al., 2010). In this case, it is quite difficult for employees to find a job close to their house. Also, concentrations of companies can be seen in airports and ports, which are regions where it is relatively impossible to hire employees whose house is close to their workplace. However, the distance, that an employee should travel in order to reach his/her work, determines the choice of that employee concerning the transportation mode he/she uses. Moreover, some other characteristics related to the location of the workplace play a key role on employees' decisions regarding the 'Home to Work Travel'. For example, a train or bus station nearby the worksite can lead a commuter to use the respective mode. Another factor is that of accessibility. Some workplaces or even municipalities are confronted with accessibility problems which might affect modal split. Various mobility initiatives do not directly depend on the strategies of a company, however, they do depend on location policies. Each municipality follows policies which strongly affect the construction of an area, the location or relocation of a company and therefore their accessibility. This means that the distribution of transport varies not only among countries but also among municipalities within a country. The study of Rietveld and Daniel (2004) showed that for short distances, municipal policies have significance in relation with bicycle use. Factors that play a key role concerning bicycle use are either natural features such as altitude differences which sometimes make it hard to cycle, or other traits like city size and infrastructure aspects that affect the security of cyclists as well as their commuting time. Therefore, the reduction of stops and supply of simple paths stimulate cycling and make it more preferred mode of transport than the car for short distances.

On the other hand, regarding large distances, even if the train is considered a faster mode than the car, commuters are discouraged to select it, when the train station is at a distance from their home which complicates the trip and leads to a waste of time. Hence, policy makers should find a way to facilitate citizens' Home-to-Work travel and provide them inducements in order to make use of a combined mode 'bike and train'.

This requires, safe and direct bike paths as well as bicycle parking spots at bus stops or train stations. The latter, is the most effective method to increase the number of bike-and-ride commuters (Martens, 2006).

2.3 Commuters' characteristics

Last but not least, the behavior of a traveler, the choice of transport as well as the influence from the mobility management is determined by many elements related to each commuter individually. Such characteristics are associated with their personality, way of life, wishes, needs and their demographic and socio-economic features (e.g. age, gender, education, income, etc). For example, people who are more open to changes are also more receptive to mobility strategies. Moreover, family oriented employees usually choose the least expensive mode of transportation or they tend to work from home more than others as they consider more important to save money and they seek to have more time close to their family. On the other hand, a materialistic commuter who has tendencies for social supremacy would prefer the comforts provided by the car rather than thinking about an alternative way of traveling that would easily satisfy their needs and will also contribute more to the environment (Cao and Mokhtarian, 2005).

2.4 The Belgian case

In the context of Mobility Management, the Belgian Government established in 2003 a three-yearly survey which is compulsory to major employers. This practically means that large Belgian companies are obliged by law to collect data concerning the commuting behavior of their employees. The collected data enable us to gain knowledge concerning mobility management measures and their effectiveness for a sustainable transport system. A study conducted by Vanoutrive (2010), which analyzed each transport modes separately, concluded that Mobility Management Measures contribute significantly to the operation of transport system. Especially, financial inducements and bicycle measures seem to be the most promising. Moreover, this study confirms that location parameters and accessibility issues play a key role in commuters' behavior.

2.5 Summary of information

The information from the existing literature can be summarized in Table 2.1, which lists characteristics of companies and/or municipalities and mobility management measures that have an impact on travel mode choices.

Mode	Location and other companies' characteristics	Mobility Managements Measures	Municipalities' characteristics
Car	Urban Fringe/accessibility problems	company cars and fuel cards	
Bike	Central City/ Urban Center	provision of bicycles/cycle mileage allowance/bicycle parking spots	safe bike paths/direct bike roots
Train	Urban Fringe/train station nearby the company	car parking charge/ extra fee and low-priced tickets	bicycle parking spots at train station
MTB	Urban Center and Residential Areas/transportation stops nearby the company	extra fee and low-priced tickets/car parking charge/information on public transport/bicycle parking spots at metro or bus stations	
Carpooling		parking places for carpooling employees/linking to a central carpool database	

Table 2.1: Key drivers for modal choices

However, analyzing each mode separately might not be the proper way, since responses are related to each other. For instance, for long distances that an employee can choose between car and train, positive drivers for train might work as negative factors for car and vice versa. In essence, if an employee chooses train for his/her daily commuting this means that he/she does not use car. Thus, analyzing each mode separately we are not able to understand how these modes are related with respect to different factors.

The present study, being conducted at a workplace level, seeks to analyze all modes simultaneously and find the determinants of commuters' behavior with respect to companies' properties.

3. DATA DESCRIPTION

3.1 HTWT Database

In the context of Mobility Management, the Belgian Government established in 2003 a three-yearly survey which is compulsory to major employers. This practically means that large Belgian companies are obliged by law to collect data concerning the commuting behavior of their employees. The questionnaire should be completed by every employer with at least 100 employees. Moreover, each employer should provide information of worksites with at least 30 employees. Therefore, the available data set contains information of worksites with at least 30 employees in Belgium in 2005. The data consist of 7460 observations (worksites) and 134 variables which capture information about the companies' characteristics (e.g. municipality, number of employees, location, sector etc), the modal split of employees, work schedules, Mobility Management measures, problems and difficulties faced by each company and some characteristics of each municipality (e.g. measure of accessibility, population density etc). Some discussions and a detailed description of these variables are necessary in order to understand the analysis in Chapter 4. The description is performed in parts given the large number of variables.

3.1.1 The dependent variable

The dependent variable, which we try to model, reflects commuters' modal choices. The information is enclosed in 9 different columnsof the data table as the number of different alternatives equals 9. In particular, these alternatives have been separated into the following main commuting modes: *Car* as a single occupant vehicle (SOV), *Carpool*, *Train*, *MTB* (Metro, Tram or Bus), transport organized by *Employer*, *Bicycle*, *Motorcycle*, *Walk* and *Other* mode. Each column indicates the percentage of employees which use the corresponding mode at a given worksite.

A first overview of the average use of each transport mode in Belgium in 2005 is provided in Table 3.1.

Transport Mode	Average Use (%)
Car	68.41
Carpool	3.33
Train	6.78
MTB	5.66

Bicycle	8.80
Motorcycle	1.82
Walk	2.96
Employer	0.54
Other mode	1.90

Table 3.1: Modal Split

As can be seen from the Table 3.1 above, by far the most preferred mode for the daily commuting to work is the car. Commuting by bicycle comes in second place, with an average use of 8.8%. Urban transport (Metro, Tram and Bus) is used by 5.66% of the commuters. Only 6.78% of the commuters use the train. Moreover, the 2.96, 1.82 and 0.54 % of commuters walk, use a motorcycle and use transportation organized by the employer, respectively. Finally, 1.90 % of the employees prefer other modes, such as a taxi or a boat.

In total, 86.4% of the companies indicated zero percent in the category `Other mode'. Only 0.7% of the companies indicated that over the 50% of their employees use other modes. Among these, there are 4 companies in which all employees use other modes. Analyzing these 57 companies separately from the whole data set, we observe that there are differences among those. The only thing we can say is that the biggest part of those companies is located in Brussels and particularly in the central city and belongs to the 'Diverse Government' sector. Probably, they use taxi or they have personal drivers. However, since we do not have individual information we are not able to extract such information. The proportion of 0.7% is too small anyway to warrant close attention.

3.1.2 Mobility Management measures

Concerning the other variables in the data set, 'Mobility Management measures' are considered the key independent variables in this study. Particularly, the data set contains information regarding 38 mobility management measures. This means that employers could declare whether they implemented one or more measures. This resulted in 38 binary variables which take the value of '1' if the corresponding measure was implemented and '0' otherwise. The motives for employees are either financially or they concern the provision of facilities and services. Some of these are bike-related measures, some others concern carpooling or public transport, or belong to a broader range of measures and are referred to as diverse measures.

The above mentioned measures are presented in the Table 3.2.

Mobility Management Measures	
Variable Name	**Description**
BicyFee	Additional cycling fee
BicySecureStorage	Secured bicycle storage
BicyFeeProfessionalTrips	Additional fee for work trips with bike
BicyBicycleforHTWT	Bicycles available for Home-to-Work travel
BicyBicyAtStation	Bicycles available at railway Station
BicyBicyclesForWorkTrips	Bicycles available for work trips
BicyRainClothes	Provision of rain clothes
BicyBetterInfrastructure	Improvement of infrastructure for bicycles
BicyCoveredStorage	Covered bicycle storage
BicyChangeRoom	Changing room
BicyShower	Showers for bicycle users
BicyPossibilityRepairBicy	Bicycle Repair Facilities
BicyBicycleMaintenance	Bicycle Maintenance
BicyInformationRoutes	Information on Cycling Routes
BicyOther	Bicycle other meausures
SUMadvanced	Number of advanced[8] measures
Cporganisation	Organisation of a carpool
CPcentralDatabse	Linking to a central carpool database
CPpreferentialParking	Preferencial parking for carpool
CPguaranteedRideHome	Guaranteed ride home
Cpinformation	Distribution of information carpool
Cpother	Carpooling other measures
PTorganisedEmployer	Public transport organized by employer
PTextraFee	Supplementary allowance for public transport
PTdiscussionwithPTprovider	Regular consultation by public transport company
Ptinformation	Information on public transport
PTworkTrips	Encouraging public transport for work related trips
Ptother	Public transport other meausres
DivCollaboration	Collaboration with enterprises
DivInformationonSOValternatives	Information on SOV alternatives
DivDiscussionswithgovernments	Collaboration with mobility institutions
DivDiscussionwithLocalGovernment	Regular Consultation with local authorities
DivTelework	Telework
DivCoordinator	Mobility coordinator
DivPaymentParking	Parking charge
DivRelocationCompany	Relocation of the site
DivFeestoMove	Relocation fee
DivFeesofGovernments	Regional or local financial measures
DivOther	Diverse Other measures

Table 3.2: Variables concerning Mobility Management Measures

3.1.3 Difficulties and problems

Some difficulties and problems encountered by employers hinder or encourage the implementation of some measures, which in their turn affects the commuters' behavior. For such reasons, employers were asked to answer questions relating to these problems.

[8] Advanced measures are considered the following: BicyBicycleforHTWT, BicyBicyclesForWorkTrip, BicyRainClothes, BicyBetterInfrastructure and BicyBicycleMaintenance.

This resulted in 29 binary variables which take the value of '1' if the corresponding problem exists and '0' otherwise. Some of these are car, bicycle or public transport related problems or they are referred as diverse problems.

The above mentioned problems are presented in the Table 3.3.

Difficulties and Problems	
Variable	**Description**
ProbCarDangerousTraffic	Dangerous traffic for car
ProbCarParkingshortage	Insufficient number of parking places
ProbCarParkingCostEmployer	High parking costs for employer
ProbCarCONGESTION	Congestion
ProbCarOther	Other car problems
ProbBicyDangerousTraffic	Dangerous traffic for bicycle
ProbBicySocialInsecurity	Unsafety (social)-bicycle
ProbBicyImage	Company Image –bicycle
ProbBicyNoPossibilityStorage	No possibilities for secured bicycle storage
ProbBicyNoShower	No showers
ProbBicyOther	Other bicycle problems
ProbPTNoInsufficientpublictrans	No or insufficient public transport service
ProbPTnofitwithworkinghours	Public transport service not adopted work hours
ProbPTtraveltime	Public Transport Travel time
ProbPTlowquality	Low quality, safety and comfort
ProbPTdistancetostop	Distance to public transport stop
ProbPTunsafeenvironment	Feeling unsafe in the neighborhood
ProbPTother	Other public transport problems
ProbDivRecruitingProblems	Recruiting problems due to bad accessibility
ProbDivCompanyCarsCost	Cost for company cars
ProbDivCostEmployerTransport	Cost of transport organized by the employer
ProbDivmandatoryETP	Not always mandatory transport plan for employers
ProbDivUnsafeRoutes	Unsafe routes
ProbDivUnsafetyHours	Feeling insecure due to work hours
ProbDivEnvironmentalProtection	Problems concerning the protection of the environment (e.g pollution)
ProbDivHealthEmployees	Problems related to employees' health (e.g stress)
ProbDivCollaborationEmployees	Problems concerning collaboration between employer and employees
ProbDivEqualityDifferentModes	Problems regarding equality among users of different modes
ProbDivOther	Other diverse problems

Table 3.3: Variables concerning Difficulties and Problems

3.1.4 Work schedules

As mentioned in the literature review in Chapter 2, work schedules influence commuters' behavior. To enable the modeling of such effects, the data set contains 4 binary variables which indicate whether a specific work schedule is applied in a company, and, in case the answer is affirmative, there are 5 other variables which provide the percentages of employees who work under the respective work schedule.

The above mentioned variables are presented in Table 3.4.

Work Schedule	
Variable	**Description**
FixedDummy	Fixed work schedule
FlexDummy	Flexible work schedule
ShiftDummy	Work schedule in shifts
IrregularDummy	Irregular work schedule
FixedWorkschedule	Percentage of employees with a fixed work schedule
FlexibleWorkSchedule	Percentage of employees with a flexible work schedule
ShiftsWorkSchedule	Percentage of employees with a work schedule in shifts
IrregularWorkSchedule	Percentage of employees with an irregular work schedule
OtherWorkSchedule	Percentage of employees with other work schedule

Table 3.4: Variables concerning Work Schedules

3.1.5 Other Company characteristics

Some other characteristics of the companies might have an impact on employees' decisions regarding the 'Home to Work Travel'. Such features are the size (number of employees), the location or the sector of the workplace. The data set contains 38 variables concerning such features. These variables are listed in Table 3.5.

Worksite's Characteristics	
Variable	**Description**
KBO_CompanyID	Crossroads Bank for Enterprises code/ KBO
ID_KBOunit	KBO units
NUTS3	Arrondissement
NUTS3fullname	Arrondissement fullname
CityRegion_SMLA	City Region of SMLA areas (Standard Metropolitan Labor Areas)
X_Lambert	X_Geographical coordinate
Y_Lambert	Y_Geographical coordinate
PostalCode	Postal Code
Municipality	Municipality
INSmunicipalityCode	Municipality Code
NACEBEL	Activity sector
DummyABC	Agriculture, Hunting, Forestry and Fishing (AB), Mining and Quarrying sector (C)
DummyD	Manufacturing sector
DummyE	Electricity gas and Water sector
DummyF	Construction sector
DummyG	Retail and related sectors
DummyH	Hotels and Restaurants sector
DummyI	Transport warehousing and Communication sector

DummyJ	Finance sector
DummyK	Real estate; renting and producer services sector
DummyL	Public administration and defense; social security insurance sector
DummyM	Educational sector
DummyN	Health and Social services sector
DummyO	Other Community; social and personal sector
DummyZ	Diverse Government sector
Core	Central City
Agglomeration	Urbanized Area
Banlieue	Urban Fringe
Forenszone	Commuter Area
outsideAgglomeration	Outer SMLA areas (Standard Metropolitan Labor Areas[9])
TRAINstation < 1 km	Number of railway stations at less than 1 km
BusStopDELIJN < 500m	Number of bus stations De Lijn[10] within 500 m
BusStopTEC < 500 m	Number of bus stations TEC[11] within 500 m
BusStopMIVB < 500 m	Number of bus stations MIVB[12] within 500 m
Employees	Number of Employees
<50employees	Less than 50 employees
50-99employees	50-99 employees
100-199employees	100-199 employees
199+employees	More than 199 employees

Table 3.5: Variables concerning the characteristics of worksites

The first two variables in Table 3.5 identify the worksite while the next eight variables are related to the location of the worksite. Specifically, KBO is the Crossroads Bank for Enterprises (BCE/KBO) which is a register for the identification of business[13]. The 'CityRegion_SMLA' variable is a categorical variable that states in which city an employer is located. Moreover, there are 14 binary variables that are related to the sector that each workplace belongs to. This practically means that companies are classified in 14 sector categories. For each sector there is a binary variable indicating whether or not a given company belongs to it. 'NACEBEL' is a string variable indicating to which specific economic sector a company belongs. Note that the 'Diverse Government' sector contains diverse types of government organizations such as police

[9] Standard Metropolitan Labor Areas include the Central city, Urbanized area, Urban fringe and commuter area
[10] Public Transport Company in Flanders
[11] Regional Public Transport Company in Wallonia
[12] Society of the Inthermunicipal Transport in Brussels (De Maatschappij voor het Intercommunaal Vervoer te Brussel)

[13] Source of business.belgium.be
http://business.belgium.be/en/managing_your_business/setting_up_your_business/main_steps/company_number/

stations, public schools and municipal offices and they are not related to any sector of NACEBEL (Vanoutrive et al., 2009). Five more binary variables indicate to which type of area (central city, urbanized area, urban fringe, commuter area and outer SMLA areas) a worksite belongs. A brief description of what is included in each area is reflected by Figure 1_3A in Appendix 3A. Useful information in order to examine commuters' behavior is whether or not a train and/or bus stations exist nearby the worksite, as well as the number of stations. Finally, the number of employees is provided as well as 4 binary variables categorizing the companies according to their size.

3.1.6 Attributes of municipalities

Last but not least, it is remarkable to recall that the mobility measures cannot produce the same successful results in all areas (Rye, 2002). Therefore, some attributes of municipalities are included.

These characteristics at municipality level are presented in Table 3.6.

Municipality Characteristics	
Variable	**Description**
slopeMunicipality	Average slope on the road network in the municipality
AccessibilityMunicipality	Accessibility measure of municipality
PopulationDensityMunicipality2005	Population density (inhabitants/km^2) of the municipality
JobDensityMunicipality2005	Job density (jobs/km^2) of the municipality
ActivePopulation2005	Population aged 20-64 in municipality
JobsActivePopulation	Jobs in municipality divided by population aged 20-64 in municipality
Population2024	Population aged 20-24 in municipality
FamChildlt6Fam	Families with children of less than 6 years old divided by number of families (municipality)
FamChildlt6HH	Families with children of less than 6 years old divided by number of households (municipality)

Table 3.6: Variables concerning the characteristics of municipalities

The physical characteristics of a site might affect commuters' behavior. For instance, areas with a hilly geography may have a negative impact on the use of cycling. Therefore, information about the average slope on the road network in the municipality was included in the data set in order to examine whether or not, and to what extent, the geography plays a role with respect to the HTWT. Also, an accessibility measure is included in the data set. The specific variable measures the accessibility of municipality. This practically means the number of individuals that can reach the municipality by car given a certain time period (Vandenbulcke et al., 2009). The smallest value of this indicator in our data set is 0.4 and the maximum value is 1.7, meaning that the greater the value of the variable the more accessible the municipality is. The variables 'population density' and 'job density' are indicators of the quality of the infrastructure of the municipality, since it might influence the effectiveness of public transportation, parking places or even congestion. Moreover, as usually younger individuals cycle more while families with small children usually avoid cycling, demographic variables are also included in the set of variables regarding the characteristics of the municipality.

3.2 Explanatory Data Analysis (EDA)

Initially, it is useful to have an overview of the data so as to ascertain how the observations are spread. For most variables, the observations are divided almost equally across the different values. However, there are some variables in which some extreme values are observed. For example, for 78.8% of the worksites, the number of employees ranges from 30 to 199, 19.4% of the worksites have 200 to 997 employees and only 1.8% of companies have 1001 to 6552 employees. Furthermore, almost half the companies apply mobility management measures. However, some measures are implemented by very few worksites, for instance the provision of bicycles at a railway station, bicycles for the HTWT, bicycle maintenance and rain clothes. The latter three measures are considered advanced measures. Also, few worksites charge the parking of cars, or take a fee for relocation of the worksite.

Subsequently, in order to understand potential differences in the behavior of commuters in different worksites and municipalities, it is useful to get an insight for some of the explanatory variables separately. The descriptive statistics provide such information.

From the Table 3.7 below, it can be seen that that 46.2% of the worksites belong to the Diverse Government sector, while the smallest fraction (just the 0.4%) belongs to the sector of agriculture, hunting, forestry and fishing (AB), mining and quarrying (C). What is more, the percentage of car users is quite high in all sectors, but a car is used less often by employees of the public administration and defense sector (L). This sector has the largest percentage of train and other mode users. Additionally, in the finance sector (J) a very high percentage of train users is observed (23.6%). Moreover, carpooling is often used in construction sector (F). The largest share of commuters who use public transport modes such as metro, bus and tram work in the hotel and restaurant sector (H). Apart from the car, in the mining and quarrying sector (C) the employees use mostly carpooling, bicycles and motorcycles. Bicycles are often used in educational (M) and diverse government (Z) sectors, while much less often in finance sector (J). In companies, which belong to the diverse government (Z) and hotels and restaurant (H) sectors, employees walk more often for their HTWT, compared with employees who work in companies which belong to other sectors.

			Average Percentage for each mode in each sector								
Activity sector	**Frequency**	**Percent**	**Car**	**Carpool**	**TRAIN**	**MTB**	**TPransportEmployer**	**Bicycle**	**Moto**	**Walk**	**ModeOther**
Agriculture, Hunting, Forestry and Fishing (AB)	12	0,2	77,8	2,3	0,4	1,5	6,9	8,8	2,3	0,3	0,3
Mining and Quarrying sector (C)	12	0,2	79,3	5,4	0,4	0	0	5,3	5,3	1,7	2,9
Manufacturing sector (D)	1092	14,6	77,9	6,8	1,5	1,4	1	7,5	2,5	1	0,8
Electricity gas and Water sector (E)	111	1,5	80,3	5,7	4,7	2,7	0	3,6	1,4	1,3	0,5
Construction sector (F)	108	1,4	69,8	10,4	1,3	1,4	11,2	3	1,4	0,5	1,2
Retail and related sectors (G)	875	11,7	77,1	1,9	2,1	6,2	0,1	5	1,7	3,3	2,6
Hotels and Restaurants sector (H)	86	1,2	59,3	2,1	5,7	18,9	0	5	2,4	3,8	3
Transport warehousing and Communication sector (I)	587	7,9	71	3,9	7,5	2,9	0,2	8,4	2,8	1,9	1,4
Finance sector (J)	182	2,4	59,6	2,6	23,6	9,2	0,1	2,5	0,6	1,1	1
Real estate; renting and producer services sector (K)	469	6,3	72,1	2,7	12,1	4,7	0,5	3,3	1,3	1,5	2
Public administration and defense; social security insurance sector (L)	18	0,2	48,4	4	26,9	7,9	0,7	4,9	0,9	2,4	3,9
Educational sector (M)	136	1,8	68	1,9	8,1	4,2	0	12,4	1,3	2,6	1,9
Health and Social services sector (N)	231	3,1	72,3	2,4	3,6	8,1	1,1	5,5	1,8	2,8	2,6

Other Community; social and personal sector (O)	96	1,3	72,9	4,2	3,7	5,7	0,2	6	3,3	2,3	1,9
Diverse Government sector (Z)	3445	46,2	62,2	2,4	8,4	7,1	0,3	12	1,7	4,1	2,2
Total	7460	100									

Table 3.7: Activity sector Frequencies and average percentage; the red and blue colors indicate highest and lowest values respectively

Additionally, it is interesting to discern differences among the geographical location of employers. The pie chart in Figure 3.1 presents the percentages of worksites in each type of area.

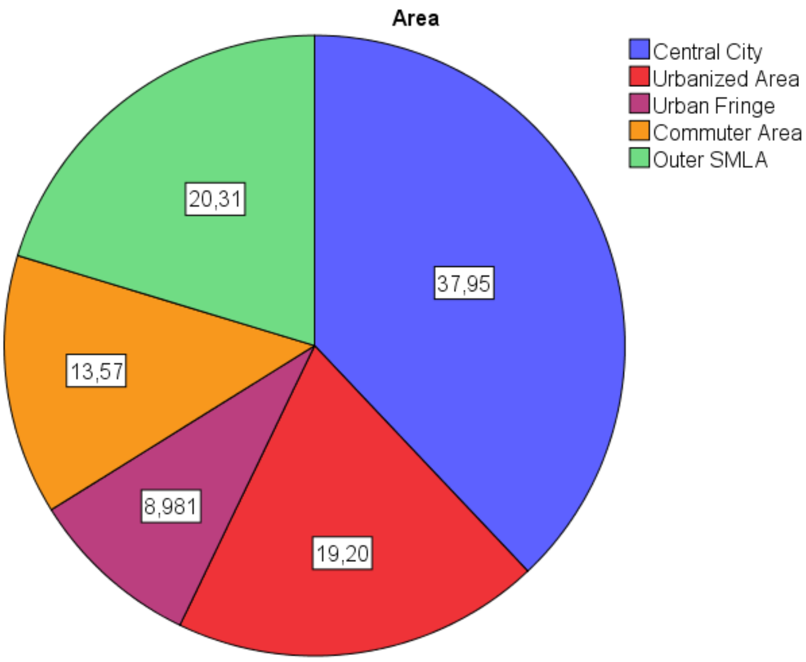

Figure 3.1: Pie chart

The largest share (37.95%) of the worksites in Belgium is located in the central city. Moreover, urbanized areas and outer SMLA areas have approximately equal shares, 19.20% and 20.31% of the total number of worksites respectively. Finally 8.981% and 13.57% of the companies can be found in urban fringes and commuter areas respectively. From the bar chart in Figure 2_3A in Appendix 3A, it can be seen that the different modes follow similar trends in each area, with the exception of public transportation (train, bus, metro and tram), the usage of which is higher in central city and urbanized areas.

Moreover, by and large, regardless the area a worksite belongs to, most companies use fixed work schedules. Flexible work schedules are applied more by worksites located in the central city or urbanized areas, while companies where employees predominantly work in shifts are located in commuter or outer SMLA regions. Finally, differences among areas with respect to irregular work schedules are not distinguished. Approximately, 30% of the employers in each region work according to an irregular schedule. The above mentioned can be verified in the Figure 3_3A in Appendix 3A, which provides the percentages of worksites that implement the various work schedules in each area. Note that a company can work with more than one work schedule and thus the percentages in each area do not add up to 100. Variables concerning working schedules are binary and take the value of '0' in case none of the employees work according to the respective work schedule and '1' otherwise.

Similarly, from Figure 4_3A in Appendix 3A, it is obvious that in all areas, most of worksites have at least 1 bus station 'De Lijn' within 500 m. Noticeable differences among areas exist in the number of bus stations 'MIVB'. More than 50% of the companies in urbanized areas have at least one MIVB bus station, while in regions outside this area, much lower rates apply. Figure 5_3A in Appendix 3A, provides the percentage of worksites that have at least two stations, regarding train and bus lines. In this case, the companies with at least two MIVB bus stations are more numerous than those with at least two stations of 'De Lijn' and 'TEC' routes, in any of the regions except for the urbanized area where companies with at least two TEC bus stations occur more frequently. Furthermore, the majority of companies with a railway station within a perimeter of 1 km lies in city centers.

From Table1_3A in Appendix 3A, it can be seen that the mobility measures that are implemented most frequently by employers, regardless of their location, are the following: additional cycling fees, secured bicycle storage, provision of changing rooms, provision of showers for bicycle users and supplementary allowance for public transport. On the contrary, inducements such as the provision of bicycles for the HTWT, the provision of bicycles at railway stations, bicycle maintenance, information on cycle routes, parking charge and relocation of the site are implemented less often. However, some more apparent differences among the regions are observed. For example, covered bicycle storages and changing rooms are provided more by companies located in commuter and outer SML areas. On the contrary, supplementary allowance for public transport measure is applied more by employers located in central city.

Moreover, in central cities there are more employers that experience car traffic problems, insufficient number of parking places, unsafe routes and problems with collaboration between employer and employees. On the other hand, in urbanized areas there are more companies experiencing problems with congestion and dangerous traffic for cyclists. Insufficient public transport service is a difficulty occurring more frequently in the urban fringe and outer SML areas. Finally, in regions outer SMLA (Standard Metropolitan Labor Areas), the employees are frequently confronted with the distance to a public transport stop. Also, according to the Figure 6_3A municipalities that belong to urbanized areas are more accessible than municipalities in other areas and also appear to have higher average slope on the road network.

Having understood the structure of the data and acquired a good picture of them, the next step of the study is to identify a proper model in order to relate the choice of transportation mode to the various types of independent variables, and identify the most influential ones.

4. METHODOLICAL FRAMEWORK

In this section, the methodology used to address the research objectives is introduced. Initially, a motivation of why the multinomial logit model (MNL) with random effects is used in this dissertation is provided. Moreover, a more technical description of the MNL model and an approximate way of building the used model are presented.

4.1 Motivation of the Spatial MNL model

Models can be categorized by the type of distribution of the response (dependent) variable which is investigated. In the present thesis, the dependent variable modeled reflects the commuters' behavior. The information is enclosed in 9 variables, each of these describes the percentage of employees using a particular type of transportation for a given company. Recall that these alternatives have been separated into the following main commuting modes: *Car* as a single occupant vehicle (SOV), *Carpool*, *Train*, *MTB* (Metro, Tram or Bus), transport organized by *Employer*, *Bicycle*, *Moto*, *Walk* and *Other* mode. In essence, at an individual level, an employee can choose among a set of categories and thus the response variable can be expressed as a categorical variable. However, for grouped data, such as company level data, which is our case, since the information on the number of the individuals using a specific mode is known for each worksite, the categorical data can be aggregated to give proportions.

When the target variable is either categorical or continuous representing proportions with values ranging between 0 and 1, logistic regression can be used. Logistic regression can be applied to both binary data (two categories) which is called 'Binomial' or 'Binary' logistic regression and when the dependent variable consists of more than two nominal outcomes. The latter case is referred to as 'Multinomial' logistic regression. The model is called a "Multinomial Logit model (MNL)" (Heij et al., 2004).

In this study, the employees' choices for their home-to-work travel are modeled. Discrete choice models are used to model the choice of one among a set of 'mutually exclusive alternatives'. The Multinomial logit model is one of the best-known discrete choice models and it is based on the concept of 'utility' (Koppelman & Wen, 1998). Utility represents the value of use you get by buying something. The greater the utility the more benefit someone get from it. Commuters choose the transportation mode with the highest utility (Bhat, 2000). Practically, the value of utility provides a way to contrast the different alternatives. Finally, the model calculates the probability of each particular outcome of the categorical response variable as a function of explanatory variables. These variables, also called predictors, can be related either to characteristics of the different alternatives or to attributes of the individual who makes the choice. In our case, the MNL model is implemented in order to compute the probability of each transportation mode as a function of the companies' properties. In other words, we seek to investigate how the characteristics of the companies (e.g. location, work schedules, size etc) and the characteristics of municipalities (e.g. accessibility) affect commuters' choices.

However, when implementing discrete choice models, there are several assumptions that should be taken into account in order to have more consistent results (Mohammadian & Kanaroglou, 2003). According to Bhat (2003), there are three major assumptions for the formulation of the Multinomial Logit model and relaxing some of them, based on the structure of the data, it is possible to end up to some alternative identifications as special cases of the MNL model. The first assumption of the MNL model concerns the random term of the utility model. In particular, the random terms are assumed to be 'Independent and Identically Distributed' (IID) with a 'type I extreme-value' or 'Gumbel' distribution. In essence, this means that the error terms do not involve common factors which are influencing the alternatives and thus are independent across the various transportation modes. In addition, these unobserved features do not vary significantly across the alternatives. In other words, there are no unobserved factors whose values fluctuate much more for one mode than for another. For instance, an unobserved factor in this study could be some characteristics of the several alternatives such as comfort. In this case, it is assumed that comfort for public transportation diverges with the same variance as for the car. Another assumption for the formulation of the MNL model is the assumption of response homogeneity. The MNL model assumes homoscedasticity and independence of the error terms. In addition, the MNL model does not allow "taste variation" at a specific variable. This means that the MNL model assumes that decision makers have the same preferences and therefore does not take into account that unobserved individuals' attributes or companies' characteristics may affect responsiveness. Finally, the MNL model does not capture correlation between individuals.

However, it is beneficial to weaken some assumptions of the MNL whenever it seems more sensible in order to obtain consistent estimates (Mohammadian & Kanaroglou, 2003). Recall that the present study is conducted at a company level and companies' characteristics are examined in order to distinguish which of them can be considered as significant factors in commuters' choices. The MNL model is based on the idea that the traveler can choose one of several alternatives. This is exactly the case of this study since the sum of the percentages of employees using a particular type of transportation for each company always sum to 1. This implies that an employee can only choose one mode and not a combination of more than one, such as the bicycle and train. Additionally, in order to avoid dependence across alternatives, since some of them are more similar than others the option of public transportation (Tram, Bus and Metro), except of train, is treated as one alternative. In case of dependence across alternatives, the model should be identified in a way to distinguish the question of whether someone uses public transportation or not and then examine the differences of these modes. This is the reason of not considering the nested logit model for this analysis. However, in order to have a more realistic approach it is necessary to take into account the spatial autocorrelation. There may be some unobserved factors that vary across some companies but are similar among some others. Workplaces that are located close to each other are related. This is referred as the so called "Spatial Autocorrelation". In particular, spatial autocorrelation is defined as "the dependency found in a set of cross-sectional observations over space", (Mohammadian & Kanaroglou, 2003). A Multilevel modeling is used when observations within the same group have similar values. Thus, in order to relax the assumption of independence across observations and capture the spatial autocorrelation, a model with random effects is required. A company is nested within an industry park which is nested within municipalities which are nested within "arrondissements" (borough) which is a level between municipality and province. However, for simplicity and assuming that companies within the same arrondissement have more or less common attributes, it is considered sufficient to capture differences in commuters' behavior across various arrondissements. Thus, to accommodate for variations in mode choices at borough level, a mixed multinomial logit model involving random effects associated with the companies' locations is considered.

4.2 Specification of the Multinomial Logit model

In the present study we cope with a dependent variable which can be expressed as a categorical variable. In this case we focus on the probability that the response variable falls in one of the available alternatives. In other words, we seek to find the probabilities that an employee chooses the several transportation modes respectively. Specifically, an employee can choose among 9 alternatives {*Car*, *Carpool*, *Train*, *MTB* (Metro, Tram or Bus), transport organized by *Employer*, *Bicycle*, *Moto*, *Walk* and *Other* mode}. Recall that we only have the percentage of employees who use a given mode. However, since we know the number of employees per company, it is easy to calculate the number of each mode users. Let π_{ij} be the probability for an individual *i* to choose alternative *j*.

$$\Pr\,[Y_i = j] = \pi_{ij} \tag{4.1}$$

where *j*= {1 ,..., m} and m represents the number of alternatives

However, in our case, since the analysis is conducted at a company level, we denote as n_i the number of employees of the i-th company. Also, Then, let s_{ij} be the number of employees of the i-th company who use the j-th mode of transport. Our data set involves 7460 companies and 9 modes of transport and therefore i= 1,..., 7460 and j= 1, ..., 9. Thus, it implies that the sum of all s_{ij} across all *j* for each company equals to n_i,

$$\sum_{j=1}^{9} s_{ij} = n_i \tag{4.2}$$

Also, the probabilities of each mode for each company *i* add up to 1,

$$\sum_{j=1}^{9} \pi_{ij} = 1 \tag{4.3}$$

However, these probabilities are not constant over companies and thus they are function of some explanatory variables x_i. In case of the multinomial logit model (MNL) this function is the logistic distribution function. In terms of this study, we seek to model the probabilities of using several transportation modes with respect to the companies' and regions' characteristics.

The MNL model takes a reference category (e.g. car) and compares it with each alternative by computing the odds $\frac{\pi_{ij}}{\pi_{iJ}}$ for all j={1 ,..., J-1}, where J denotes the reference category. Then, the MNL model assumes that the log-odds follow a linear model, defined as follows:

$$log\frac{\pi_{ij}}{\pi_{iJ}} = \alpha_j + x_i'\beta_j = \eta_{ij}\ , \qquad (4.4)$$

where α_j is a constant, β_j is a vector of parameters for alternative j and x_i' is a vector of explanatory variables for the i-th company. However, the exponentiation of the above equation directly produces the probabilities π_{ij},

$$\pi_{ij} = \frac{exp(\eta_{ij})}{\sum_{k=1}^{m} exp(\eta_{ik})}, \qquad \text{for j= \{1,..., m\}} \qquad (4.5)$$

4.3 Concept of Utility

In cases where we seek to model several choices (discrete choice models) the structure of the model is based on the concept of 'utility'. Let U_{ij} denotes the utility (value) that the i-th individual gets by using the j-th alternative. Utilities may depend on individuals' characteristics and/or on alternatives' attributes. The present study is conducted at an aggregated level, focuses on the companies' characteristics and U_{ij} can be identified by the following equation:

$$U_{ij} = u_{ij} + \varepsilon_{ij} = a_j + x_i'\beta_j + \varepsilon_{ij} \qquad (4.6)$$

where u_{ij} reflects the utility of transport mode j for individuals working at company i with characteristics x_i; β_j is a vector of parameters for alternative j and x_i' is a vector of explanatory variables for the i-th company. The last term ε_{ij} is the error term and represents the unobserved factors concerning companies' attributes that are related with employees' preferences.

Normally, an individual chooses the option that provides the greater utility. Thus, an individual employed by the i-th company will use the mode of transport that gives him/her the highest utility. This implies to the following:

$$\pi_{ij} = Pr[y_i = j] = Pr\left[u_{ij} + \varepsilon_{ij} > u_{ik} + \varepsilon_{ik}, for\ all\ k \neq j\right]$$

or

$$\pi_{ij} = Pr\left[\max\left(U_{i1,}U_{i2,\dots,}U_{im}\right) = U_{ij}\right] \tag{4.7}$$

Assuming that the error terms follow the 'Gumbel' distribution and that they are 'independently and identically distributed' IID for all i and j, it has been proven that the probability of someone from company i choosing the j-th option equals

$$\pi_{ij} = \frac{exp(u_{ij})}{\sum_{k=1}^{m} exp(u_{ik})} \tag{4.8}$$

The latter equation constitutes the fundamental equation of the Multinomial Logit model (see equation 4.5). In our case, π_{ij} can be interpreted as the probability of an employee who is working at the i-th worksite to use the j- th mode of transport.

Furthermore, by taking the log-odds of probabilities of each alternative versus the reference category 'J' and by replacing u_{ij} with $x_i'\beta_j$ we have the following:

$$log\left[\frac{Pr[y_i=j]}{Pr[y_i=J]}\right] = (a_j - a_J) + x_i'\left(\beta_j - \beta_J\right) \tag{4.9}$$

The latter equation verifies that the MNL model is based on the so called assumption of 'Independence of Irrelevant Alternatives'. As it can be seen, the log-odds of two alternatives is not influenced by other options. This requires that the several transport modes should be significantly different from each other in order to implement the multinomial logit model. As it was mentioned before, public transportation modes (Metro, Bus and Tram) are considered as one category.

4.4 Estimation of the Multinomial Logit model

The aim, so that we can compare the several alternatives with respect to the companies' characteristics, is the estimation of the β_j parameters included in the utility formula in the component of $x_i'\beta_j$ where x_i' is (z x 1) vector of explanatory variables and β_j is (z x 1) vector of parameters for option j. For the Multinomial Logit model, where the probability distribution of multivariate responses is given by the multinomial distribution, the parameter estimation is carried out by maximizing the Multinomial likelihood with probabilities π_{ij} in which the utilities are included (see equation 4.8). Specifically, the complete likelihood is given by the following equation:

$$L = \prod_{i=1}^{n} \prod_{k=1}^{n_i} \pi_{i1}{}^{d_{k1}} \ \ \pi_{i2}{}^{d_{k2}} \ \dots \ \pi_{im}{}^{d_{km}} \tag{4.10}$$

Where n is the number of the worksites, n_i is the number of employees of the i-th company and d_{kj} is an indicator which takes the value of 1 when the k-th employee in company i chooses transport mode j and 0 otherwise, for j= 1, ..., m. However, the above formula can be written as follows:

$$L = \prod_{i=1}^{n} \pi_{i1}{}^{\sum_{k=1}^{n_i} d_{k1}} \ \pi_{i2}{}^{\sum_{k=1}^{n_i} d_{k2}} \dots \pi_{im}{}^{\sum_{k=1}^{n_i} d_{km}} \tag{4.11}$$

Moreover, as d_{kj} is an indicator which takes the value of 1 when the k-th employee chooses the j-th transport mode and 0 otherwise, the following sum $\sum_{k=1}^{n_i} d_{kj}$ equals the number of employees working at company i and use mode j. If this sum is denoted by s_{ij} with j= 1,..., m, the complete likelihood becomes

$$L = \prod_{i=1}^{n} \pi_{i1}{}^{s_{i1}} \ \pi_{i2}{}^{s_{i2}} \dots \pi_{im}{}^{s_{im}} \tag{4.12}$$

4.5 Incorporating Random Effects in the MNL model

In order to have a more realistic approach, it is necessary to account for spatial autocorrelation. It is assumed that the utilities of companies from the same borough (arrondissement) are correlated since they may have common unobserved factors affecting employees' commuting behavior. Thus, assuming that these unobserved factors are independent of observed companies' characteristics, random effects at borough level should be included in the model in order to account for dissimilar sources of variability.

In essence, we try to capture for unobserved heterogeneity by allowing for each borough to have a specific intercept in the model for each alternative. A company can belong to one of the 47 boroughs of Belgium.

Incorporating random effects in the MNL model the utilities are given by the following equation:

$$U_{kij} = u_{kij} + \varepsilon_{kij} = \alpha_{kj} + x'_{ki}\beta_j + \varepsilon_{kij} \tag{4.13}$$

where $\alpha_{kj} \sim N\left[\alpha_j, \sigma^2_{\alpha_j}\right]$ and $\varepsilon_{kij} \sim N[0, \sigma^2_{\varepsilon}]$

U_{kij} can be interpreted as the utility of mode of transport *j* for an individual employed by the i-th company which belongs to k-th borough. Also, α_{kj} are unobservable effects for the k-th borough and transport mode *j*, β_j is a vector of parameters for alternative *j*, x'_{ki} is a vector of explanatory variables reflecting characteristics of the i-th company that belongs to k-th borough. Finally, ε_{kij} is independent and identically distributed over *k, i, j,* error term following the Gumbel distribution. The random effects model requires independency between the random effects α_{kj} and the regressors x'_{ki} (Cameron & Trivedi, 2005).

The probability conditional on the random term α_{kj}, which captures unobserved heterogeneity among boroughs, of an employee who is working at the i-th worksite with characteristics x_{ki} (k borough), to use the *j*- th mode of transport is now defining by the following equation:

$$Pr[t_{ki} = j | x_{ki,}\alpha_{kj}] = \pi_{kij} = \frac{exp(\alpha_{kj} + x'_{ki}\beta_j)}{\sum_{l=1}^{m} exp(\alpha_{kl} + x'_{ki}\beta_l)} \tag{4.14}$$

where m is the number of different alternatives.

Restricting that the variance of the borough term for the baseline category is zero, the random term α_{km} equals zero for all k boroughs, where m is the reference category (Bhat, 2000). Thus, the unconditional probability can be defined as follows:

$$Pr[t_{ki} = j] = \int_{\alpha_{k1}=-\infty}^{+\infty} \dots \int_{\alpha_{k(m-1)}=-\infty}^{+\infty} \frac{exp(\alpha_{kj} + x'_{ki}\beta_j)}{\sum_{l=1}^{m} exp(\alpha_{kl} + x'_{ki}\beta_l)} dF(\alpha_{k_1}) \dots dF(\alpha_{k(m-1)}) \tag{4.15}$$

where F is the cumulative normal distribution.

In case of random effects, for the parameters' estimation, the likelihood function of all companies *i* in borough *k*, conditional on α_k (α_k = $(\alpha_{k1}, \dots, \alpha_{km-1},)'$) term becomes:

$$L_k | a_k = \prod_{i=1}^{n_k} \pi_{ki1}{}^{s_{ki1}} \ \pi_{ki2}{}^{s_{ki2}} \dots \pi_{kim}{}^{s_{im}} \tag{4.16}$$

where (s_{ki1} … s_{im}) is the number of employees working at the i-th company located at the k borough and using the 1st, 2nd,…, and the m-th mode respectively.

The unconditional likelihood function of all companies *i* in borough *k* takes the form:

$$L_k = \int \left(\prod_{i=1}^{n_k} \pi_{ki1}{}^{S_{ki1}} \ \pi_{ki2}{}^{S_{ki2}} \dots \pi_{kim}{}^{S_{im}} \right) \mathrm{g}\left(\alpha_{k,} \Sigma\right) d\alpha_k \qquad (4.17)$$

where $\mathrm{g}(\alpha_k, \Sigma)$ is the density function of α_k. It is needed to specify the distribution of the unobserved heterogeneity α_k, and usually it is assumed the normal distribution (Cameron & Trivedi, 2005). Since in the MNL model, we use a reference category, we assume that the utility for this mode is '0'. For all other utilities that should be specified, the random effect is involved. Thus, taking as a reference the "car" alternative, α_k = $(\alpha_{kcarpool}, \alpha_{ktrain}, \alpha_{kMTB}, \alpha_{kbike}, \alpha_{kwalk}, \alpha_{kemployer}, \alpha_{kmotorcycle}, \alpha_{kothermode})'$. Also, the α_k is distributed according to a multivariate Normal distribution with expectation '0' and covariance matrix Σ so that $\alpha_k \sim N(0, \Sigma)$.

Finally, the unconditional likelihood function of all *k* boroughs equals:

$$L = \prod_{k=1}^{r} \int \left(\prod_{i=1}^{n_k} \pi_{ki1}{}^{S_{ki1}} \ \pi_{ki2}{}^{S_{ki2}} \dots \pi_{kim}{}^{S_{im}} \right) \mathrm{g}\left(p_{k,} \Sigma\right) d\alpha_k \qquad (4.18)$$

The above formula is the multiplication of the likelihood contribution of the *k-th* borough, for k=1 ...r, where, r is the number of boroughs types and n_k is the number of worksites belonging to *k-th* borough so as $\sum_k^r n_k = 7460$ as the total number of companies. The integral should be after the multiplication across the different boroughs in order to ensure that each borough type has different constants α_k.

Maximizing the likelihood function (4.18) with respect to the parameters provides the estimates of the covariance matrix Σ and also the estimates that are included in the equation (4.14) for the calculation of probabilities for each transportation mode with respect to the companies' attributes while distinguishing differences across several areas. In case of high dimensional problems the solution of these integrals requires simulation techniques (Monte Carlo Integration) while for low dimensional problems numerical integration is feasible (Colin & Trivedi, 2005). In our case, we used 'borough' random specific effects which leads to the computation of 47 integrals, since the number of the various areas is 47. Moreover, seeking to simplify the problem we reduced the number of alternatives m from 9 to 5 by considering only the most widely used transport modes(car, carpool, train, MTB and bike). This leads to m-1 dimensions which implies to low dimensional problem. For low dimensional integration, in particular less than 4, the quadrature method is considered a good approximation method for the computation of the integrals (Bhat, 2000). Specifically, in the present thesis, the used integration method is the adaptive Gaussian quadrature method.

4.6 Model Selection Criteria

Inclusion of more variables in a model will always improve the fit of that model. However, this can lead to overfitting. To decide on the performance of a model, information criteria are used. These criteria express the model fit and the number of parameters.. The “Akaike Information Criterion (AIC)” and “Schwarz Criterion (SBC) (i.e. Bayesian Information Criterion or BIC)” provide an operational way to equilibrate the complexity of a model against how well the model fits the data, as they penalize a model for lack of parsimony (i.e. over parameterization or over fitting) (Colin & Trivedi, 2005).

The AIC is given by

$$\mathrm{AIC} = -2.\log(\mathrm{likelihood}) + 2\mathrm{p}, \tag{4.16}$$

while the BIC is given by

$$\mathrm{BIC} = -2.\log(\mathrm{likelihood}) + \mathrm{p}.\ln(\mathrm{n}), \tag{4.17}$$

where p is the number of parameters to be estimated in the equation and n is the number of observations. The lower the values of AIC and BIC the better the fit of a model.

5. MODELING PROCESS & RESULTS

Initially, in this section the data pre-processing analysis is described. Specifically, due to the high number of variables, a factor analysis was conducted before the core analysis with the intention of reducing dimensionality while retaining only relevant variables in order to make model estimation more manageable. In subsection 5.2, the strategy followed for the model selection is described. Finally, in subsections 5.3 and 5.4 the results of the MNL model and of the extended MNL with random effects are presented respectively.

5.1 Data pre-processing analysis

5.1.1 Principal component analysis (PCA)

Some pre-processing and additional adjustments of the initial data set were required before starting the analysis. Some new variables were computed according to principal component analysis in order to smooth the progress of the analysis and the exploitation of the data. Principal component analysis (PCA) is a method that is meant to create linear combinations of the original variables so that these linear combinations are uncorrelated to each other and explain a large portion of variance of the original variables.

Therefore, starting from a set of correlated variables, we obtain a set of uncorrelated variables, which is something that is considered very useful in statistical methods. Moreover, PCA allows us to recognize the new variables (components) by giving them names and to observe which of the original variables have been most influential to them.

In this study, we seek to create linear combinations of variables concerning work schedules and also mobility management measures for each mode respectively. Therefore, we conducted different PC analyses for working schedules as companies can implement more than one work schedule which makes them not independent from each other. Thus, we considered that an efficient way to reduce dimensionality is to take their interactions via representative and informative new components. Moreover, we ran a PCA for bike, carpool, public transport (PT) and diverse measures. We always began with all the original variables; however we excluded some of them due to the fact that the factor solution should explain at least half of each original variable’s variance in order not to lose much information. We seek to keep as much information it is possible in order to create representative components. However, the original variables which were excluded from PCA, were included in the analysis for the model estimation. The results from PC analyses are summarized in Table1_5A, Table2_5A and Table3_5A, in the Appendix 5.1A, which present the components' score coefficients of each variable.

Specifically, in the Table 1_5A in the Appendix, it can be seen that 2 components were created as a combination of 4 various work schedules. The first component is strongly and positively correlated with fixed scheduling and thus it represents this type of working plans while at the same time it is negatively correlated with flexible working hours. This means that usually, whenever a company works with fixed working hours, flexible work arrangements are not allowed for employees and vice versa. On the contrary, the second informative factor is represented more by non-irregular working plans and work arrangements in shifts. These two factors constitute the most informative combinations regarding work schedules.

Furthermore, according to the Table 2_5A in the Appendix 5.1A, regarding bicycle measures, we end up to 3 components that can be used instead of the original ones included in the PC analysis. As it can be seen from the above mentioned table the first component exhibits stronger correlation with the following types of measures; showers for bicycle users, changing room and covered bicycle storage. Therefore a reasonable name for this component is 'Bike facilities'. Following the same process for the next two components, the second and third component represents 'Bike Provision' and 'Cycling Fee' respectively.

Consequently, we reduce dimensionality and we end up with 3 instead of 8 variables included in PCA. Each of those components contains information about all 8 original variables. In essence, some variables exhibit stronger correlation than others. For instance, it can be concluded that, usually, when a company has showers for bicycle users, it also provides changing room and covered bicycle storage. Also, when bicycles are provided to employees for their HMTW travel, also bicycle maintenance is provided and vice versa.

Additionally, for mobility measures related to carpooling, public transport and other measures, only one component was extracted. Specifically, according to the Table 2_5A in the Appendix 5.1A, one new variable named as 'Carpool Organization' was created representing the following measures: Organization of carpooling, linking to a central carpool database and distribution of carpool information. Moreover, for measures regarding public transportation, a new component, named 'PT information', was created reflecting regular consultation by public transport company and information on public transport. Finally, concerning diverse measures, 3 closely related variables (information on SOV alternatives, collaboration with mobility institutions and regular consultation with local authorities) formed a new component which we named 'Diverse discussion with Government' (see Table 3_5A in Appendix 5.1A).

The new variables that can be used instead of those that had been involved with PC analyses are summarized in the Table 5.1 below.

Factor	Represents
Fixed Schedules	Fixed Scheduling
	No Flexible Arrangements
Regular & Shifts	No Irregular scheduling
	Work arragnements in shifts
Bike facilities	Covered bicycle storage
	Changing room
	Showers for bicycle users
Bike provision	Bicycle Maintenance
	Bicycles available for Home-to-Work travel
Cycling fee	Additional cycling Fee
	Additional fee for work Trips with bike
	No other bike facilities
Carpool organization	Organisation of a carpool
	Linking to a central carpool database
	Distribution of information carpool
PT information	Regular consultation by public transport company
	Information on public transport
Diverse discussion with government	Information on SOV alternatives
	Collaboration with mobility institutions
	Regular Consultation with local authorities

Table 5.1 New factors/variables from PCA

5.1.2 Formation of the data

As we have already mentioned in Chapter 2, the dependent variable is enclosed in 9 different columns as the number of different alternatives equals 9. Each column indicates the percentage of employees which use the corresponding mode at a given worksite. However, only the 5 alternatives were used as options that we seek to model. Thereafter, to enable the encoding process of the analysis, we created a new data set with 5 observations per company. Thus, we end up to a data set with number of observations equals 7460 multiplying by 5 which implies to 37300 observations. Moreover, 2 new variables were created. The first variable was named as 'mode' and indicates the transportation mode. The 5 observations per company have 5 different values for the 'mode' variable and the same values for the explanatory variables. Then we defined the 'weight' variable that indicates the percentage (at scale of 100) of commuters who used a given mode among the 5 alternatives. As it can be seen from SAS commands in the Appendix 5.2A we used the weight variable in the 'replicate' statement of nl mixed procedure. In this way, we accounted for the differences in the modal split among companies. However, rows where the weight variable equaled with 0, were deleted from the data set as they were considered non informative.

5.2 Data cleaning & model selection strategy

Initially, a few variables were considered as unnecessary and were excluded from the study. For example, the variables 'ID_KBOunit', 'PostalCode' 'X_Lambert' and 'Y_Lambert' were excluded, as they are unique for almost every worksite and thus do not contribute to our analysis since we assumed that regions within the same arrondissement have the same random effects and thus correlations across neighboring locations are ignored. Variables 'KBO_CompanyID', 'INSmunicipalityCode' and 'NUTS3fullname' were also redundant because other variables conveyed the same information. Moreover, in order to simplify the analysis, some transportation modes were not modeled: only the following 5 alternatives were used as options; car, carpool, train, MTB and bicycle. The other alternatives were removed from the analysis. Recall that motorcycle, transport by employer and other modes were used by few employees while it was considered that 'walking' as an option depends much more on the distance that an employee needs to travel and thus on the place they live and not on mobility management measures or the infrastructure of an area. Moreover, as already discussed in Chapter 4 (methodological framework) the MNL model requires a reference category and compares it with each alternative by computing the odds of their probabilities. In the present study, a sensible reference alternative is car as we seek to find ways to motivate or help employees to diminish car usage. Thus, the reference category is the 'Car' in order to directly compare it with other transportation modes. Also, for categorical variables such as ‘Sector’ variable and ‘Commuter Area’ it was necessary to select a baseline category, as the reference, so as to make model estimation and interpretation feasible. In this case, ‘Dummy_O; Other Community, Social and Personal’ and ‘Urban Fringe’ were selected as reference categories for ‘sector’ and ‘commuter area’ variables respectively.

To develop our model, we followed the data analysis strategy displayed in Figure 5.1.

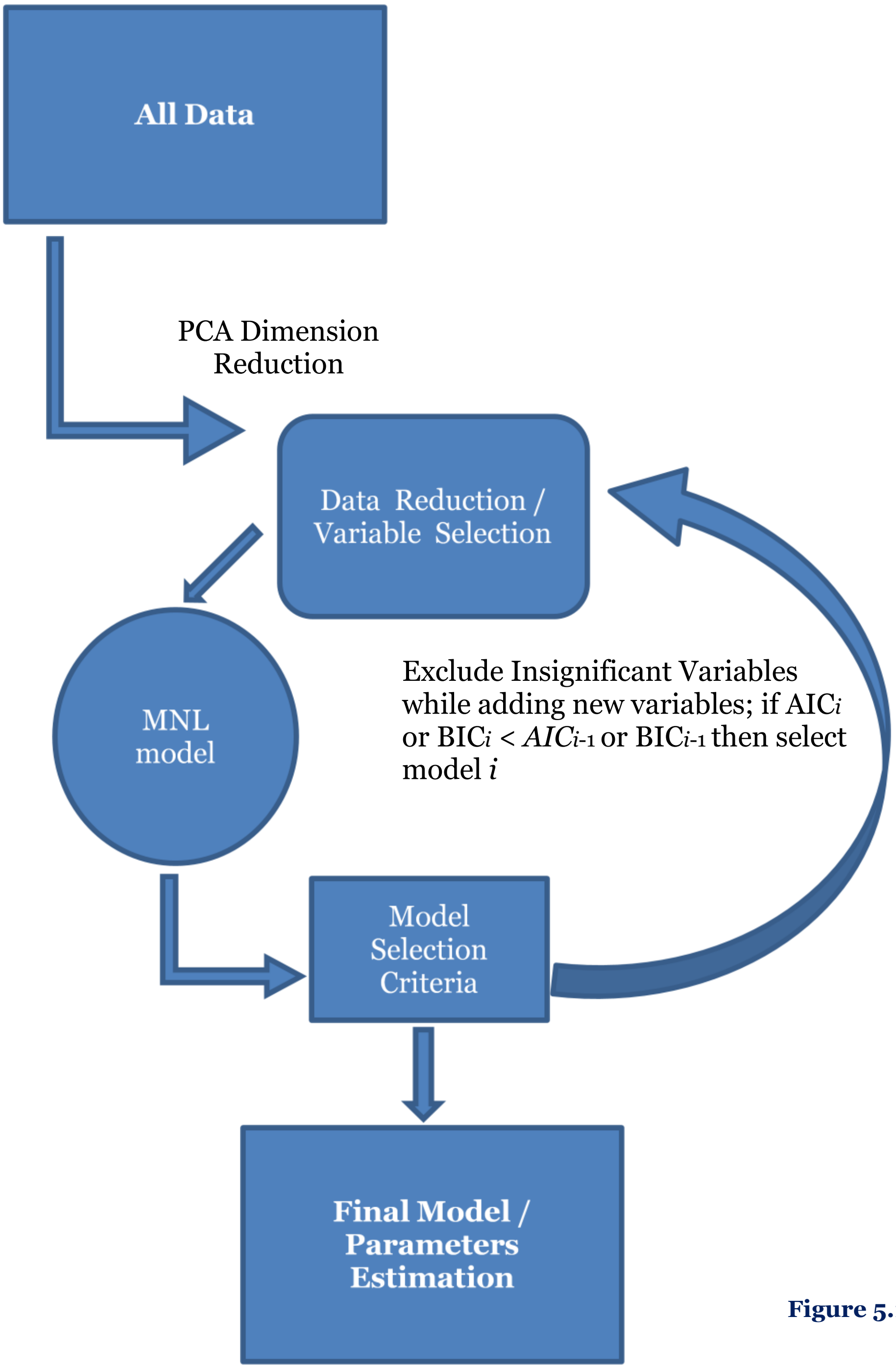

Figure 5.1 Model selection process

We used SAS 9.1 software and particularly the non-linear mixed procedure (proc nlmixed) which has the capability to estimate multinomial models with random effects. Our model is considered a complex model since we seek to incorporate more than 100 variables. The nl mixed syntax is not easy, since it is necessary to define sensible starting values for the parameters, otherwise, initial values which are not close to reality and therefore do not work for the data, lead to convergence problems. Starting values were specified intuitively or coefficients from previous study (Vanoutrive, 2010) were used whenever they were available. However, each time we run a new model we re-specified the initial values using the estimates from the latest model.

After having ignored the redundant explanatory variables while creating some new ones and after having set the reference category, only some of the explanatory variables were selected, intuitively and rationally, for the formation of the utilities of the several alternatives for the first model. After estimating the first MNL model, insignificant and non informative variables were excluded from the model while new variables were incorporated. To assure that the most appropriate model has been selected in order to describe the factors that most significantly have an impact on the employees' choice for their HTWT; model fit was assessed through the Akaike Information Criterion (AIC) as well as the Bayesian Information Criterion (BIC) as defined in (4.16) and (4.17) in Chapter 4. Initially, we implemented a multinomial logit model without random effects trying to include as many significant and informative variables it was possible taking into account the above criteria. Thereafter, we incorporated random effects in the multinomial logit model. In this case, we focused only on variables regarding mobility management measures, difficulties and problems encountered by employers and municipalities' characteristics in order simplify the model. SAS commands for both models are provided in the Appendix 5.2A.

5.3 MNL model Interpretation

After selecting the final model, which was considered the most proper one in order to determine which variables are most useful in explaining employees' choices, the interpretation of the results follow in this section.

In Table 4_5A in the Appendix 5.1A the specification of the model is presented. After 143 iterations for the minimization of the negative log-likelihood the algorithm successfully converged.

The final model includes the variables presented in Table 5.3 and Table 5.4. The original output with detailed information about parameter estimates, its standard errors and p_values, is provided in Table 5_5A, Table 6_5A, Table 7_5A and Table 8_5A in the Appendix 5.1A, for each mode (carpool, train, MTB and bike) separately.

As already mentioned the multinomial logit model uses a reference category and compares it with each alternative by computing the log-odds of their probabilities. In our case the baseline category is the 'car' mode. The parameter estimates concern coefficients of the explanatory variables encountered in the utilities for each alternative (see equation 4.9 in Chapter 4). Thus, the above mentioned tables demonstrate to what extend a one-unit increase in a variable affects the relative log-odds of probabilities of each mode versus car. All comparisons are made "ceteris paribus"; that is, given that all the other characteristics/variables are held constant. However, the exponentiation of each coefficient was computed in order to directly obtain the odds ratio and to compare the probabilities more easily.

According to Table 5.3, the size of a company is positively correlated with the relative log odds probabilities of carpool, train and MTB vs. car. On the other hand, the size of a company is negatively correlated with the log odds of choosing bike versus car. However, the coefficients of the 'size' variable for bike and MTB utilities are really small. Specifically, a one unit increase in 'log size' variable is associated with a 0.568 , 0.397 and 0.068 increase in the relative log odds of choosing carpool, train and MTB vs. car respectively, while, a one unit increase in 'log size' variable is associated with a 0.061 decrease in the log odds probability of bike vs. car. Therefore, the larger the company is the larger the probability for an employee to choose carpool and train compared to car is. Although the same applies for MTB, the effect is really small. Differently, using the odds ratio, probabilities could be interpreted directly. In this case, the odds ratio for a one unit increase in variable 'FFixedSchedule' is 1.019, 0.735, 0.939 and 1.046 for choosing carpool, train, MTB and bicycle vs. car respectively. Recall, 'FFixedSchedule' variable is the factor computed by PCA and represent fixed scheduling with no flexible arrangements. Thus in essence, we conclude that for companies where employees work more with fixed work schedules, the probability to use carpool rather than car is increasing. The same implies for bicycle as well while the probability to choose train or MTB is decreasing. However, the effects for bike and MTB are very small. For non-irregular working plans and work arrangements in shifts, the probability of using carpool vs. car is increasing and specifically much more than fixed scheduling. Again, for MTB the probability is decreasing but with no big differences vs. car. For train and bicycle this variable was insignificant with alpha level of significance 0.05 and thus was excluded from the analysis.

The same process in interpretation is followed for all the variables in the model. Therefore, regarding sectors, the relating log odds of choosing carpool versus car will be increased by 0.172, 0.965, 0.379 if the company belongs to electricity gas and water, construction and public administration compared to the baseline category 'Other Community, Social and Personal' sector respectively. Recall, that in Chapter 2, it was mentioned that the construction sector has the largest percentage of carpool users. On the contrary, the probability of using carpool versus car is larger for the rest sectors compared to the baseline category and particularly most distinct differences imply for education, retail and health and social services. Concerning train, for employees working in a company that belongs to finance, public administration and defense, real estate, transport warehousing or diverse government (such as police station or municipal offices) the probability to choose train versus car is significantly higher. On the other hand, for agriculture, hunting, fishing, manufacturing and construction sectors the probability of choosing train versus car is significantly lower compared to the Other Community, Social and Personal' sector. Regarding public transportation (MTB), it is obvious that only for sectors related to government, social services, public administration and hotels and restaurants, compared to the Other Community, Social and Personal' sector, the probability of using MTB vs. car is larger. Finally, the probability of using bicycle vs. car is significantly higher if the company belongs to sectors related with hotels and restaurants, transport warehousing, public administration, and much more to diverse government or educational compared to the reference category. Recall that the educational sector has the highest number of cyclists. In construction and finance sectors companies, employees are more likely to use car instead of bike compared to Other Community, Social and Personal sector.

Furthermore, concerning variable 'area', significant differences are observed between the different levels and the reference category 'Urban Fringe'. Recall that the baseline level corresponds to the suburbs of a city. Central city and urbanized area are closer to the core of the city region comparing to the suburbs while commuter area is more remote area. Outside SMLA is the farthest area since it is even outside the city region. If the variable 'central city', 'urbanized area', 'commuter area' and 'outside SMLA' will be increased by one unit (binary variables, from 0 to 1) the log odds for choosing carpool vs. car would expected to be larger by 0.240, 0.171, 0.231 and 0.258 respectively compared to suburbs. Moreover, the relative log odds of using train vs. car will be increased by 1.393, 1.371 and 0.156 if moving from suburbs to central city, urbanized area and commuter area respectively. It is obvious that for areas closer to the core of city region the probability of choosing train instead of car is higher. On the contrary, for outside SML areas the probability is lower, but the estimate is not significant in the 0.05 level. Also, the log-odds of choosing MTB vs. car is considerably higher for central city and more for urbanized areas comparing to the suburbs. This might be confirmed also due to the fact that problems related to insufficient public transportation service, occur more often in urban fringe areas (see Chapter 2). On the contrary, for the log odds of using bike vs. car major changes do not occur. However, we can mention that for central city, commuter area and outside SMLA the probability of choosing bicycle vs. car is larger than in suburbs, while it is lower if the company belongs to urbanized areas. Recall, that urbanized areas show greater levels in the slope on the road network which might be a reason and also there are more companies experiencing problems with congestion and dangerous traffic for cycling. While in central cities there are more employers that experience car traffic problems and insufficient number of parking places.

Finally, if the accessibility of municipality by car will be increased by one unit the log odds of using train and bike vs. car decreases by 0.299 and 0.544 respectively.

PARAMETER	Parameter Estimates							
	Carpool (2)		Train (3)		MTB (4)		Bike (5)	
	Log odds ratio	odds ratio	Log odds ratio	odds ratio	Log odds ratio	odds ratio	Log odds ratio	odds ratio
Alpha	-3,968		-5,126		-4,447		-1,361	
LogSize	0,568	1,765	0,397	1,488	0,068	1,070	-0,061	0,941
FfixedSchedule	0,019	1,019	-0,308	0,735	-0,063	0,939	0,045	1,046
FregularShiftSchedule	0,210	1,234	.	.	-0,026	0,974	.	.
Agriculture, Hunting, Forestry, Fishing, Mining and Quarrying	-0,326	0,722	-1,382	0,251	-1,242	0,289	0,103	1,109[!]
Manufacturing	0,021[!]	1,022	-1,043	0,352	-1,323	0,266	0,031	1,032[!]
Electricity gas and Water	0,172	1,187	-0,240	0,787	-1,278	0,279	-0,396	0,673
Construction	0,965	2,625	-1,002	0,367	-1,445	0,236	-0,666	0,514
Retail	-0,641	0,527	-0,866	0,421	-0,265	0,767	-0,105	0,900
Hotels and Restaurant	-0,155[!]	0,856	0,172	1,188	1,106	3,021	0,219	1,244
Transport warehousing and Communication	0,063[!]	1,065	0,586	1,797	-0,758	0,469	0,376	1,456
Finance	-0,340	0,712	0,786	2,194	-0,067[!]	0,936	-0,412	0,662
Real estate; renting and producer service	-0,405	0,667	0,668	1,950	-0,542	0,582	-0,345	0,708
Public administration and defense; social security insurance	0,379	1,461	1,602	4,961	0,415	1,514	0,441	1,555
Educational	-0,637	0,529	0,519	1,681	-0,530	0,589	0,718	2,051
Health and Social services	-0,666	0,514	-0,250	0,779	0,239	1,269	0,095	1,099[!]
Diverse Government	-0,339	0,713	0,580	1,786	0,191	1,211	0,839	2,314
Central city	0,240	1,271	1,393	4,028	1,334	3,798	0,180	1,197
Urbanized area	0,171	1,186	1,371	3,939	1,443	4,233	-0,048	0,954
Commuter area	0,231	1,259	0,156	1,169	-0,403	0,668	0,082	1,086
Outside SMLA	0,258	1,294	-0,002[!]	0,998	-0,443	0,642	0,179	1,196
AccessibilityMunicipality	.	.	-0,299	0,742	.	.	-0,544	0,581

Table 5.3: MNL Parameter estimates; !Not significant at 5% level

What is more, other variables that correspond to the same model are considered significant in commuters' behavior. Such variables concern mainly mobility management measures or potential problems that companies are facing. Table 5.4 provides such information.

The log odds of choosing carpool vs. car if there is 'Guaranteed ride home', 'Organisation of a carpool' and 'Linking to a central carpool database' are expected to increase by 0.236, 0.156 and 0.2, respectively. In essence these mobility management measures contribute to the increase of carpooling versus car. On the contrary, 'Distribution of information for carpool' does not increase the utility of carpool. Also, preferential parking for carpool users was dropped from the model because it was insignificant variable.

Also, problems related with car congestion will increase the probability for an employee to choose going to their work together with the car of his/her colleague. Finally, if there is a train station within 1 km the probability of using carpool is declining, but it has little of importance relatively with car.

Furthermore, the existence of a train station within 1 km from work plays a major role regarding employees' choices for either train or car. The log odds for using train instead of car would expect to be increased by 1.055. Also, problems related with car congestion and parking costs for employer increase the probability to choose train vs. car, however with much less effect than the train station.

Measures such as information providing on public transport, public transport organized by employer and supplementary allowance for public transport increase the probability of choosing MTB vs. car. Also, an important factor in boosting public transport usage instead of car is the existence of a bus station within 500m and also the number of bus stations contribute to the MTB usage but with much less importance. However, if there is a problem with travel time using PT the probability of using car in that case vs. MTB is larger.

Finally, employees are more likely to choose bicycle for their home to work travel when companies use as motivation financial measures and bike provision. However, the effects of these measures are very small. Particularly , when variables 'FBikeProvision' and 'FCyclingFee' as formed by PCA, will be increased by one unit the log odds for choosing bike vs. car is increased by 0.033 and 0.036 respectively. On the contrary, initiatives regarding bike facilities such as covered storage, changing room and showers, do not affect employees' preferences since the estimates for these parameters is insignificant at the 1% level of significance. Dangerous traffic and the sense of social insecurity for bicycle users negatively affect bike selection vs. car. However, the major factor that is negatively associated with the log odds of using bike instead of car is the slope on the road network in the municipality. Particularly, a one unit increase in the log slope will decrease by -3.123 the log odds. It is also noteworthy that measures like provision of rain clothes and provision of bicycle for work related trips were dropped from the model since they were not significant.

Parameter	Carpool (2)	
	Log odds ratio	odds ratio
CPguaranteedRideHome	0,236	1,266
Cporganisation	0,156	1,169
CPcentralDatabase	0,200	1,221
Cpinformation	-0,344	0,709
ProbCarCONGESTION	0,222	1,248
DTrainstationwithin1km	-0,050	0,951

Parameter	Train (3)	
	Log odds ratio	odds ratio
DTrainstationwithin1km	1,055	2,871
ProbCarCONGESTION	0,170	1,185
ProbCarParkingCostEmployer	0,169	1,184

Parameter	MTB (4)	
	Log odds ratio	odds ratio
FPTInfo	0,0284	1,0288
PTorganisedEmployer	0,1477	1,1592
PTextrafee	0,0242	1,0245
ProbPTtraveltime	-0,1192	0,8876
ProbPTunsafeenvironment	0,2849	1,3296
NBusStopswithin500m	0,0685	1,0709
DBusStopwithin500m	0,9862	2,6810

Parameter	Bike (5)	
	Log odds ratio	odds ratio
FBikeFacilities	-0,003[!]	0,997
FBikeProvision	0,033	1,034
FCyclingFee	0,036	1,037
ProbBicyDangerousTraffic	-0,070	0,932
ProbBicySocialInsecurity	-0,104	0,902
LogSlopeMunicipality	-3,123	0,044

Table 5.4: MNL Parameter Estimates; !Not significant at 5% level

The above can be summarized in Table 5.5. It illustrates the increase or decrease of the utility for each mode vs. car with respect to important factors. A decrease corresponds to a negative sign, whereas an increase corresponds to a positive sign. A double arrow indicates stronger effect, approximately when the absolute value of log odds is 1 or greater than 1.

Variable	Category level	log odds Carpool	log odds Train	log odds MTB	log odds Bike
Size	Size	↑	↑		
Work schedule	Fixed	↑	↓	↓	
Sector; baseline: Community, Social and Personal	Agriculture, Hunting, Forestry, Fishing, Mining and Quarrying	↓	↓↓	↓	
	Manufacturing sector		↓↓	↓↓	
	Electricity, Gas and Water sector		↓	↓↓	↓
	Construction sector	↑	↓↓	↓↓	↓
	Retail and related sectors	↓	↓	↓↓	↓
	Hotels and Restaurants sector			↑↑	
	Transport warehousing and Communication sector		↑	↓	↑
	Finance sector	↓	↑		↓
	Real estate; renting and producer services sector	↓	↑	↓	↓
	Public administration and defense; social security insurance sector		↑↑	↑	
	Educational sector	↓	↑	↓	↑
	Health and Social services sector	↓	↓		
	Diverse Government sector	↓	↑↑	↑↑	↑
Area; baseline: Suburbs	Central City		↑↑	↑↑	
	Urbanized area		↑↑	↑↑	
	Commuter area			↓	
	Outside SMLA		↓	↓	
Infrastructure	DTrainstationwithin1km		↑↑		
	DBusStopwithin500m			↑↑	
	LogSlopeMunicipality				↓↓
problems	b_ProbCarCONGESTION	↑	↑		
	ProbCarParkingCostEmployer		↑		
	ProbBicyDangerousTraffic				↓
	ProbBicySocialInsecurity				↓
	ProbPTtraveltime			↓	
Mobility management measures	FBikeProvision				↑
	FcyclingFee				↑
	PtorganisedEmployer			↑	
	CpguaranteedRideHome	↑			
	CpcentralDatabase	↑			

Table 5.5 Summary of changes in relative utility for the different level of factors

5.4 Extension of MNL model with Random Effects

To take into consideration the correlation in commuters' behavior for employees working to worksites located close to each other, random effects were involved in MNL model. As already discussed in Chapter 4, it is assumed that companies from the same borough (arrondissement) yield correlated responses since they may have common unobserved factors affecting employees' commuting.

When incorporating random effects difficulties regarding the computation of the integrals were encountered and the execution time was long. Thus, it was deemed appropriate to diminish the dimensions and simplify the model. Therefore, some variables like 'sectors' and 'size' were excluded. The specification of the model is provided in Table 9_5A in the Appendix. The model now has 55 parameters instead of 106 parameters in the simple MNL model presented in the previous section. Also, a random effect was specified for each mode, except for the reference category. The random effect captures the unobserved impact of the borough and is assumed to be Normally distributed.

In particular, u = (u2, u3, u4, u5) ~ N(0, Σ), where Σ is the covariance matrix.

$$\Sigma = \begin{bmatrix} \mathrm{Var}_2 & \mathrm{Cov}_{23} & \mathrm{Cov}_{24} & \mathrm{Cov}_{25} \\ \mathrm{Cov}_{32} & \mathrm{Var}_3 & \mathrm{Cov}_{34} & \mathrm{Cov}_{35} \\ \mathrm{Cov}_{42} & \mathrm{Cov}_{43} & \mathrm{Var}_4 & \mathrm{Cov}_{45} \\ \mathrm{Cov}_{52} & \mathrm{Cov}_{53} & \mathrm{Cov}_{45} & \mathrm{Var}_5 \end{bmatrix}$$

where, $\mathrm{Cov}_{ij} = \mathrm{Cov}_{ji}$ for each i and j, where $i \neq j$.

The estimated variances and covariances are provided in Table 11_5A in the Appendix 5.1A. However, the interpretation of the above estimates is provided later in this section.

Variables which are most useful in explaining commuters' behavior are summarized in Table 5.7 and Table 5.8. In general, although the MNL model with random effects does not include all the variables included in the model presented in the previous subsection, some similarities in the trends are observed. According to the Table 5.7, fixed scheduling is positively associated with carpooling and cycling while it is negatively associated with train and public transportation. In particular, a one unit increase in variable "Fixed Scheduling" will increase the log odds of choosing carpool and bike vs. car by 0.115 and

0.103 respectively. On the other hand, a one unit increase in the same variable will decrease the log odds of using train and MTB vs. car by 0.065 and 0.042 respectively.

Also, non irregular and working plans in shifts are positively correlated with carpooling while it decreases the probability of using MTB instead of car. For train and bicycle, this variable was insignificant.

Concerning the areas, although the trends are the same, the MNL without random effects indicated greater estimates, in absolute values, for carpool, train and MTB while smaller estimates for bike. This practically means that the area, in the case of random effects, has less effect on choosing carpool, train and MTB vs car. On the contrary, the effect of the area on choosing bicycle vs car is higher in case we account for unobserved heterogeneity across boroughs. In particular, if the variable 'central city', 'urbanized area', 'commuter area' and 'outside SMLA' will be increased by one unit the log odds for choosing carpool vs. car would be expected to increase by 0.123, 0.080, 0.120 and 0.106 respectively compared to suburbs. These variables are binary which take the value of 1 if a given worksite belongs to the respective area and 0 otherwise. This practically means that a one unit increase in a categorical variable regarding an area corresponds to the fact that a given company is located to this area. Therefore, the utility of carpooling vs. car is decreasing in suburbs compared to other areas. Moreover, the relative log odds of using train vs. car will be increased by 0.895, 0.306, 0.433 and 0.264 if moving from suburbs to central city, urbanized area, commuter area and outside of SMLA respectively. For the core area the probability of choosing train instead of car is increasing. Also, the log-odds of choosing MTB vs. car is substantially larger for central city and also for urbanized areas comparing to the suburbs. Finally, the log odds of using bike vs. car is increasing for all areas except of urbanized area compared to the suburbs. Especially, within central city the probability of using bike vs. car is increasing much more than in other areas.

After accounting for spatial correlation, accessibility of municipality is not a significant factor to explain commuters' choices regarding carpooling, train and MTB. However, it is positively associated with cycling. This means that accessible municipalities contribute more to bicycle use than to car use, however, the effect is relatively small. Note that the MNL model without random effects indicates negative sign for this estimate.

Parameter	Parameter Estimates							
	Carpool (2)		Train (3)		MTB (4)		Bike (5)	
	Log odds ratio	odds ratio	Log odds ratio	odds ratio	Log odds ratio	odds ratio	Log odds ratio	odds ratio
Alpha	-1,057		-1,590		-1,301		0,516	
Fixed Scheduling	0,115	1,122	-0,065	0,937	-0,042	0,959	0,103	1,108
FregularShiftSchedule	0,287	1,332	.	.	-0,065	0,937	.	.
Central City	0,123	1,131	0,895	2,447	0,421	1,523	0,364	1,439
Urbanized Area	0,080	1,083	0,306	1,358	0,239	1,270	-0,111	0,895
Commuter Area	0,120	1,128	0,433	1,542	-0,091	0,913	0,112	1,118
Outside SMLA	0,106	1,111	0,264	1,302	-0,424	0,654	0,080	1,083
AccessibilityMunicipality	.	.	-0,010!	0,990	.	.	0,087	1,091

Table 5.7: MNL model with random effects - Parameter Estimates ; !Not significant at 5% level

According to the Table 5.8, the log odds of choosing carpool vs. car if there is ‘Guaranteed ride home’, and ‘Organization of carpooling’ are expected to be larger by 0.175 and 0.169 respectively. Also, problems related with car congestion will also increase the probability by 0.022. However, the existence of train a station within 1 km from the worksite decreases the probability of using carpool instead of car.

Regarding train mode vs. car, the log odds probabilities due to a one unit increase in “train station within 1 km”, “car congestion problems” and “car parking costs” will be increased by 1.547, 0.035 and 0.040 respectively. Also, when employers give employees an extra fee when they use public transportation, this contributes more for choosing MTB instead of car while a bus station nearby the company plays the major role.

Finally, financial motivation for bike constitutes the main measure from the company side in order to motivate employees to choose bike vs. car. However, bike related dangerous traffic and social insecurity problems were considered insignificant factors in explaining employees’ choices while the model presented in the previous subsection indicated negative but small effect of these factors. On the contrary, the slope on the road network and job density decrease the utility of bike.

Parameter	Carpool (2)	
	Log odds ratio	odds ratio
CPguaranteedRideHome	0,175	1,191
Cporganisation	0,169	1,184
ProbCarCONGESTION	0,022	1,023
DTrainstationwithin1km	-0,071	0,931

Parameter	Train (3)	
	Log odds ratio	odds ratio
DTrainstationwithin1km	1,547	4,697
ProbCarCONGESTION	0,035	1,036
ProbCarParkingCostEmployer	0,040	1,041

Parameter	MTB (4)	
	Log odds ratio	odds ratio
FPTInfo	0,0160	1,0161
PTextrafee	0,1115	1,1180
ProbPTtraveltime	0,0193	1,0195
DBusStopwithin500m	0,5942	1,8116

Parameter	Bike (5)	
	Log odds ratio	odds ratio
FBikeProvision	0,029	1,029
BicyFee	0,041	1,041
ProbBicyDangerousTraffic	0,006!	1,006
ProbBicySocialInsecurity	0,016!	1,016
SlopeMunicipality	-0,201	0,818
LogJobDensityMunicipality2005	-0,200	0,819

Table 5.8 MNL with random effects - Parameter Estimates !Not significant at 5% level

According to the parameter estimates of the covariance matrix provided in Table 5.9, the variance of the random effect for carpool is really small. This implies that regarding carpooling there are no substantial variations among boroughs. This applies for MTB and bicycle too since their variances are also relatively small. On the contrary, unobserved factors in boroughs differ regarding train since its variance is higher. Moreover, the covariance of train and MTB is relatively high which means that unobserved factors for train and MTB are correlated. Covariance among other modes are tiny which implies that are unobserved factors concerning different boroughs are independent among these transportation modes. Especially, the covariance of bicycle and carpool is not significant.

Parameter	Estimate	Pr > |t|
Var(carpool)	0.005848	<.0001
Var(train)	0.1086	<.0001
Var(MTB)	0.02033	<.0001
Var(bike)	0.01409	<.0001
cov(train-carpool)	-0.02224	<.0001
cov(MTB-carpool)	-0.00327	0.0021
cov(MTB-train)	0.02121	<.0001
cov(bike-carpool)	-0.00050	0.6327
cov(bike-train)	-0.00740	0.0127
cov(bike-MTB)	-0.00569	<.0001

Table 5.9 Parameter Estimates for covariance matrix of random effects

Additionally, Tables 12_5A, 13_5A, 14_5A and 15_5A in the Appendix, provide the parameter estimates of random effects for each borough for carpool, train, MTB and bicycle respectively. In particular, in Maaseik and Genk there are unobserved factors that significantly increase the utility of carpool while in Brugge, Leuven and Gent there are unobserved factors that significantly decrease the utility of carpool. On the contrary, in Masseik, Genk, Turnhout and Hasselt there are unobserved factors that decrease the utility of train while in Brussels, Brugge, Gent and Leuven some unobserved factors increase the utility of train. Moreover, in Zinnik and Brussels there are unobserved factors that increase the utility of MTB while the same applies in Leuven for bicycle. Finally, in Mons and Charleroi there are unobserved factors that decrease the utility of bicycle while for MTB the same applies in Kortrijk and Genk.

6. CONCLUSIONS & DISCUSSION

The goal of this study was to analyze commuters' behavior with respect to companies' properties in Belgium. Daily commuting or alternatively the "Home to Work Travel" (HTWT) constitute the major cause of congestion. Policies based on demand management seem to be vital in order to reduce the negative outcome of transport. Such approach is called 'Mobility Management' and it seeks to provide a solution to congestion-related difficulties via various tools and strategies. However, the daily commuting to work is closely connected with the respective company and its properties (e.g. location, mobility management measures etc.). Mobility management measures are mobility policies on the part of companies whose main aim is to establish and improve a sustainable transport system. Financial inducement, provision of facilities and parking management play a fundamental role in mobility management (Laurent Van Malderen et al. 2011). In particular, the present study seeks to discern which factors related with companies' characteristics have a significant impact in employees' choices.

Specifically, this study focused on Belgium and its large companies. The available data set contains information of worksites with at least 30 employees in Belgium in 2005. The data of this study, being collected at a workplace level, consists of 7460 observations (worksites) and 134 variables which capture information about the modal split of employees which is the variable to be explained, companies' characteristics (e.g. municipality, number of employees, location, sector etc), work schedules, mobility management measures, problems and difficulties faced by each company and some characteristics of each municipality (e.g. measure of accessibility, job density, slope on the road network etc).

For the purpose of modeling the modal choices, a discrete choice model was implemented. We proceeded in our analysis with two parts. First, a Multinomial Logit model was built for analyzing employees' choices. Then, taking into account spatial autocorrelation a mixed multinomial logit model involving random effects was considered. In essence, we tried to capture for unobserved heterogeneity by allowing for each borough (arrondissement) to have a random intercept in the model for each mode. A company can belong to one of the 47 boroughs of Belgium. In the analysis 5 transport modes were involved. These are car, carpooling, train, MTB (metro, tram and bus) and bicycle. As reference category 'car' mode was selected in order to directly compare it with the other transport modes.

The results confirmed more or less what is known from the literature. Specifically, they showed positive correlation with the size of a company and carpooling, train and much less with MTB versus car. Apparently, the greater the number of employees the greater the probability of finding someone whose direction matches with another colleague. Thus, for big companies carpooling promotion could be more efficient than in small companies. On the other hand, the larger the company is, the greater the probability of choosing car versus bicycle. Also, regarding working schedules, the results are very similar to a previous study by Vanoutrive (2010). Specifically, fixed scheduling is positively associated with carpooling and bicycle instead of car, although no big differences were detected. On the contrary, flexible work plans contribute more to train use than to car use. In essence, for someone who lives far away from his/her work and their options are car and train, they will choose the train more easily if their work schedule is flexible. On the other hand, if there is time pressure car is more convenient. The same applies for MTB but with less impact. For regular working schedules in shifts carpooling is increasing vs. car while public transportation is not preferred.

Regarding sectors, for "agriculture, hunting, forestry, fishing, mining and quarrying" and for the retail sector car is the preferred mode of transport comparing to all modes. Also, in real estate and finance sector employees tend to use the car more than any other mode except for train. On the other hand, in "public administration and defense" and "diverse government" sectors the probability of using car is lower and especially compared with train and bicycle respectively. Employees tend to choose carpooling instead of car in construction sector. Public transportation is considerably larger in "hotels and restaurant" sector while cycling is increasing in educational sector.

Furthermore, comparing different areas with suburbs, employees whose work is located in central city tend to use the car less, especially compared with train and public transportation. The same applies for urbanized areas except for the bicycle case but with no big difference vs. car. This can be explained by the fact that suburbs indicate more often problems related with insufficient public transportation service while urbanized areas show greater levels in the slope on the road network and indicate more often problems related with dangerous traffic for cycling. In commuter areas, train is the least used transportation mode. On the other hand carpooling is used less often in suburbs and considerably larger in commuter and outside SML areas. Cycling vs. car, apart from urbanized areas, is increasing in all areas compared with suburbs, however not with wide differences. This means that other factors, more significant than areas, affect bike usage vs. car.

Moreover, efficient measures to promote carpooling were considered 'Guaranteed ride home', and 'Organization of carpooling'. The distribution of information regarding carpool was considered an insignificant factor, while, Vanoutrive (2010) showed that this measure is negatively correlated with carpooling. Also, problems related with car congestion will also decrease the probability of using car instead of carpooling. Finally, the existence of train station within 1 km from the worksite decreases the probability of using carpool instead of car, which is also confirmed by Vanoutrive (2010). Probably, an employee would consider more the train as an alternative than carpool, otherwise they would use their car. In other words, whenever there is no train station close to someone's work, the utility of carpooling is increasing and mobility management measures should be considered more for diminishing car usage.

Also, the existence of train station within 1 km from the worksite constitutes the major factor for increasing train usage vs. car. Moreover, other factors related more with car would make train more preferable. These concern "car congestion problems" and "car parking costs". This can be confirmed from a previous study (Vanoutrive, 2010). Specifically, the results of the above mentioned study showed that financial measures or the distribution of information regarding public transportation do not have a significant effect on increasing train use. On the contrary, public transportation extra fee contributes more for choosing MTB instead of car while a bus station nearby the company plays the major role.

In other words, if a new train station will be created in an area, the utility of train is increasing and thus more employees would choose train for their HTWT. Specifically, assuming that all the other variables will remain constant, most of these employees would be former car users but also carpoolers since the utility of carpool would be smaller. Additionally, if car congestion is a problem in this area, the utility of carpool is increasing while the utility of train is increasing a bit more.

Regarding cycling mobility management measures such as the provision of facilities do not play a key role in increasing cycling. Vanoutrive (2010) showed a negative relation between provision of facilities and bicycle usage. On the contrary, the results of the present study confirmed that financial inducements from the company would motivate employees to choose bike vs. car. Negative determinants, with large effect on cycling, are related with the infrastructure of municipality and particularly these are the slope on the road network and job density, which is also confirmed by Vanoutrive (2010). In essence, if there is high level of the slope on the road network and also of job density in an area, employees would consider more the car than bicycle for their HTWT. However, if a new bus station will be created in this area car users would choose the bus.

Finally, the MNL model with random effects showed that there are some unobserved factors that differ among boroughs which have an impact in employees' choices regarding train. In particular, in Masseik, Genk, Turnhout and Hasselt there are unobserved factors that decrease the utility of train while in Brussels, Brugge, Gent and Leuven some unobserved factors increase the utility of train. Also, there are some unobserved factors, common within the same borough, which are correlated more for train and MTB. The latter applies in Brussels and Genk. The utility of train and MTB increases in Brussels while it decreases in Genk. These factors may concern differences among boroughs in peoples' perceptions about public transportation.

7. LIMITATIONS

A number of limitations apply to this analysis as it was based on some practical restrictions. In order to make the analysis more feasible, we simplified the model. Initially, the least important transportation modes were not modeled and thus only the main 5 modes were included in our study. In addition, in order to account for spatial autocorrelation, it is considered more appropriate to implement multilevel modeling, when observations within the same group have similar values. As already discussed, a company is nested within multiple levels (industry park which is nested within municipalities which are nested within borough. However, in the present study for simplicity it was assumed that companies have more or less common attributes only within the same borough. Correlations across neighboring locations were ignored. Also, as already mentioned in Chapter 5, we defined a 'weight' variable that indicates the percentage (at scale of 100) of commuters who used a given mode among the 5 alternatives. Thereafter, we used the weight variable in the 'replicate' statement of nl mixed procedure. Another, option is to use as weight variable the number of employees who use a given mode which might lead to more precise results. However, the size of companies varies among worksites and particularly the values of the 'size' variable range from 30 to 6552. Thus, considering that using the number of employees as 'replicate' variable on the one hand would complicate the execution of the model and also would give more weight to big companies than to small companies, we used the percentage of employees as 'weight' variable.

In addition, some other restrictions that could be considered for further research as well, concern the available information. Conducting the analysis at a company level, we were not able to include other possible significant factors. As already discussed in section 2, transportation choices are also determined by many elements related to each commuter individually. Such characteristics are associated with their demographic and socio-economic features (e.g. age, gender, education, income, etc) as well as to their place of living. Modal choice depends on the distance that should be travelled and also the travel time that each mode consumes. Last but not least, factors concerning the several alternatives (e.g. cost) were also not accounted for in the analysis.

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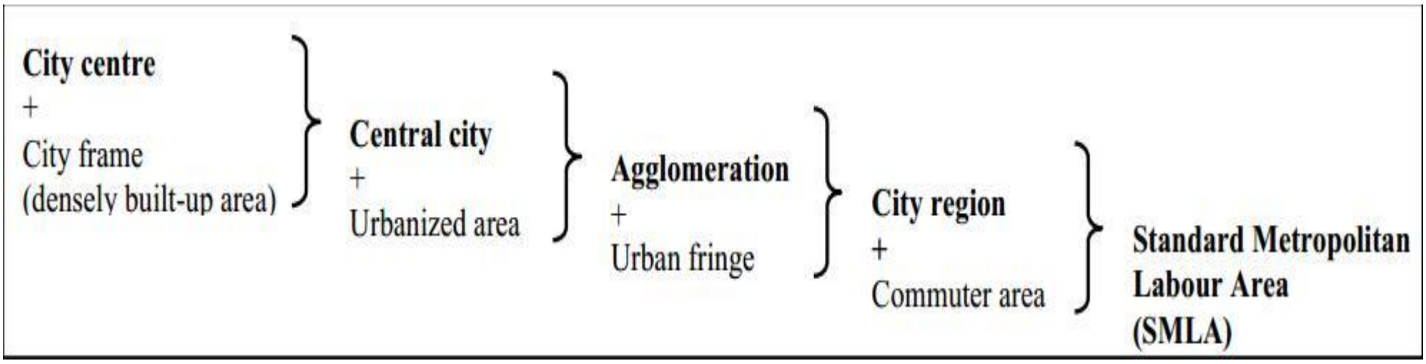
APPENDIX

3A. Data Description

Figure 1_3A



Source: Verhetsel Ann, Thomas Isabelle, Beelen Marjan- *Commuting in Belgian metropolitan areas: the power of the Alonso-Muth model.* Journal of Transport and Land Use - ISSN 1938-7849 - 2:3/4(2010), p. 109-131

Figure2_3A

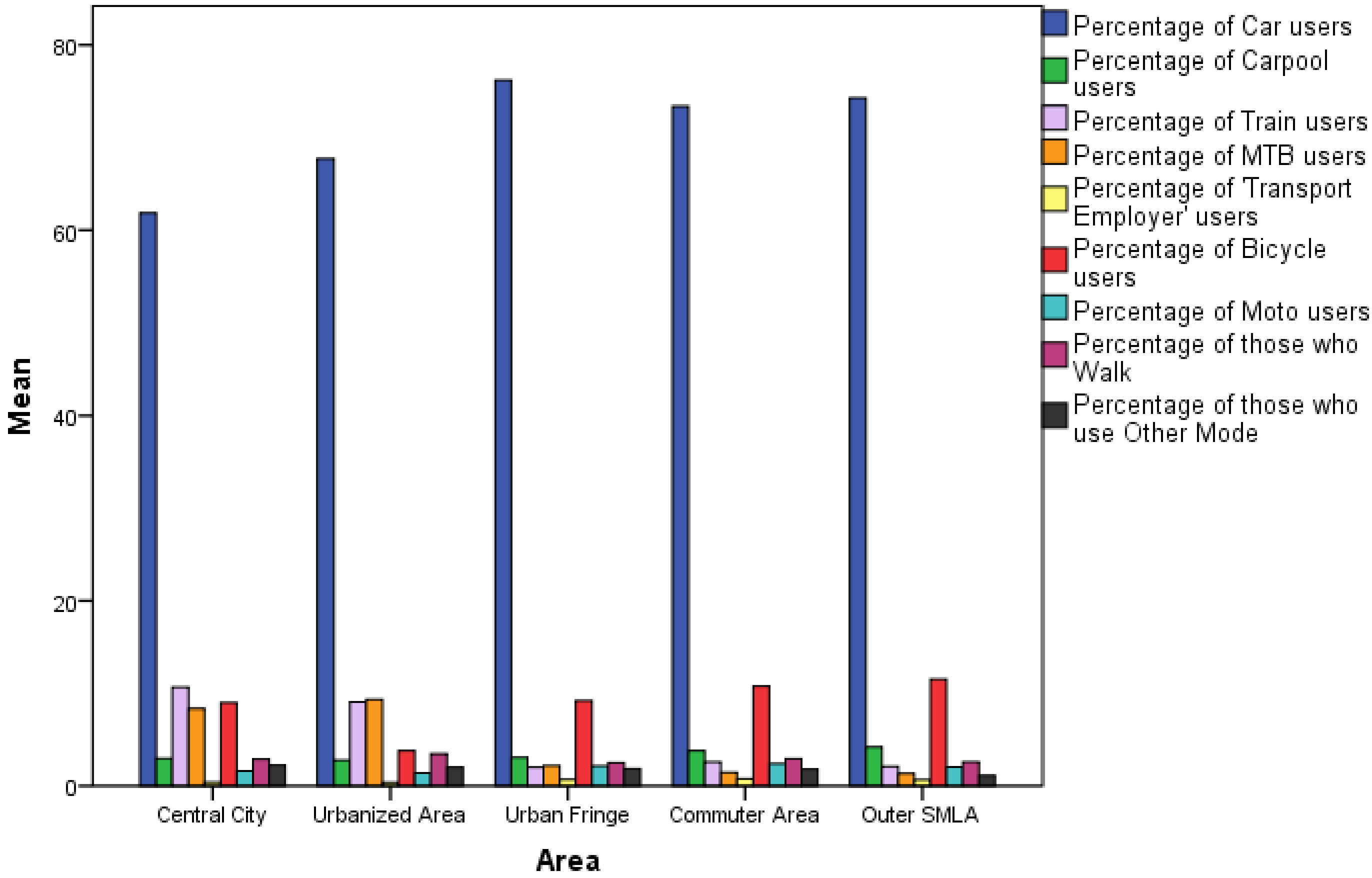


Figure 3_3A

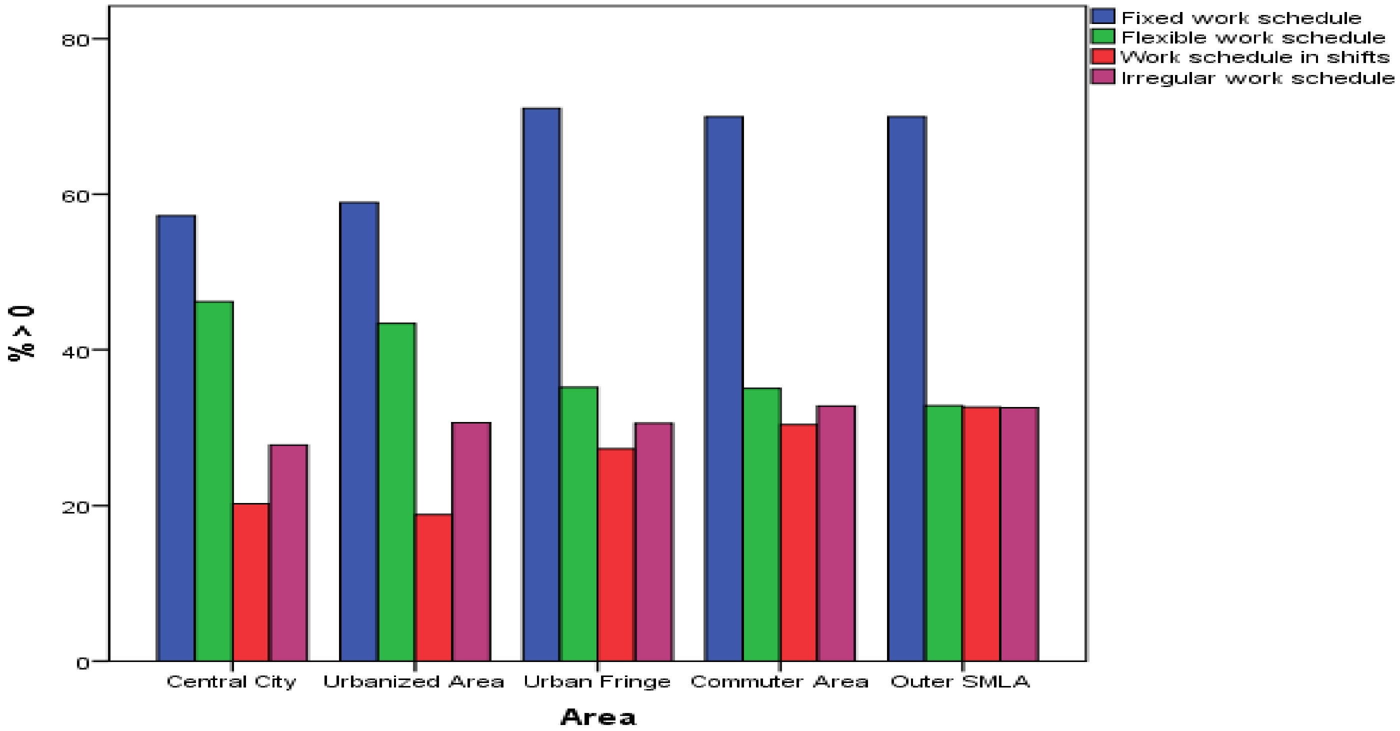


Figure 4_3A

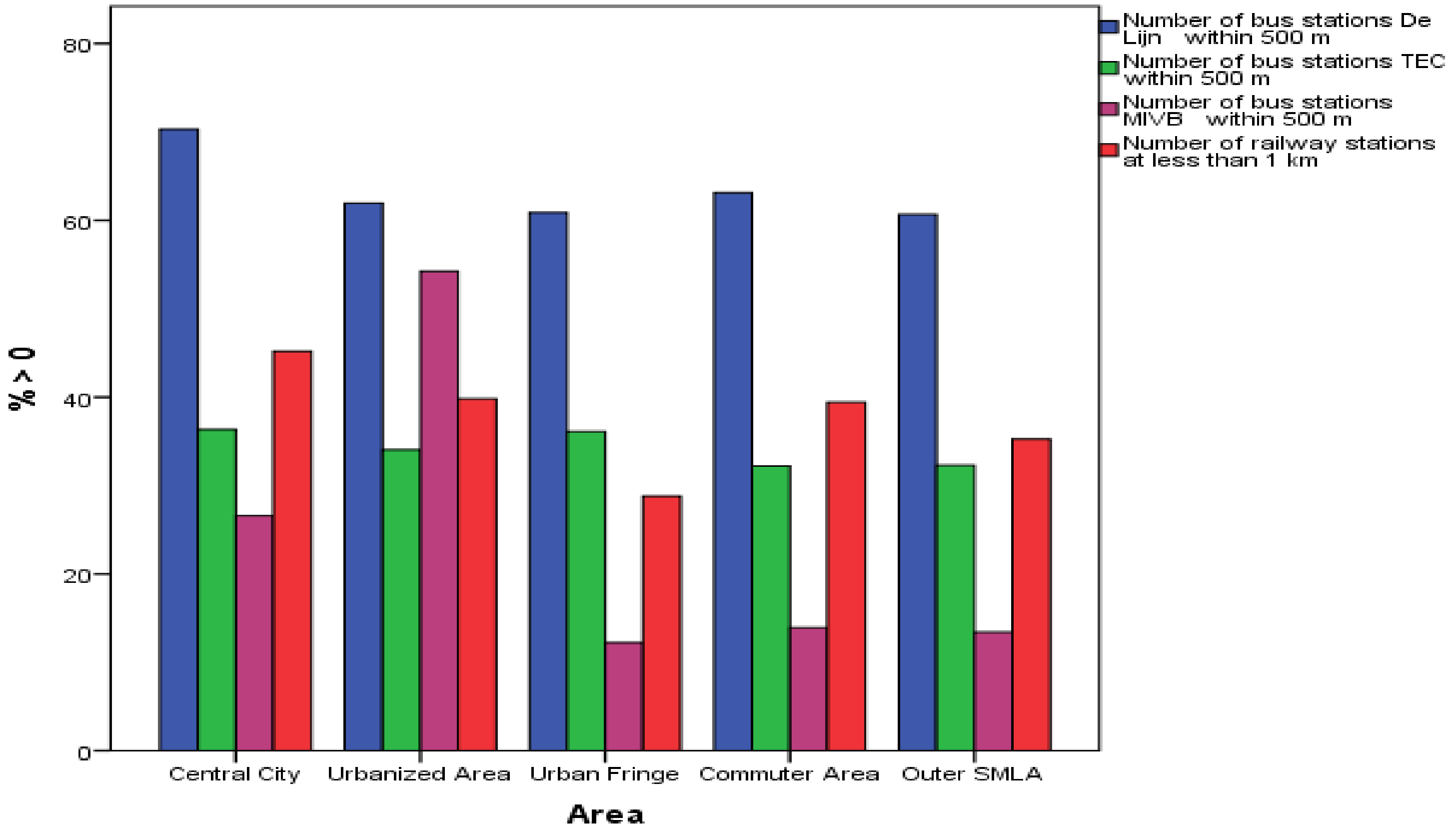


Figure 5_3A

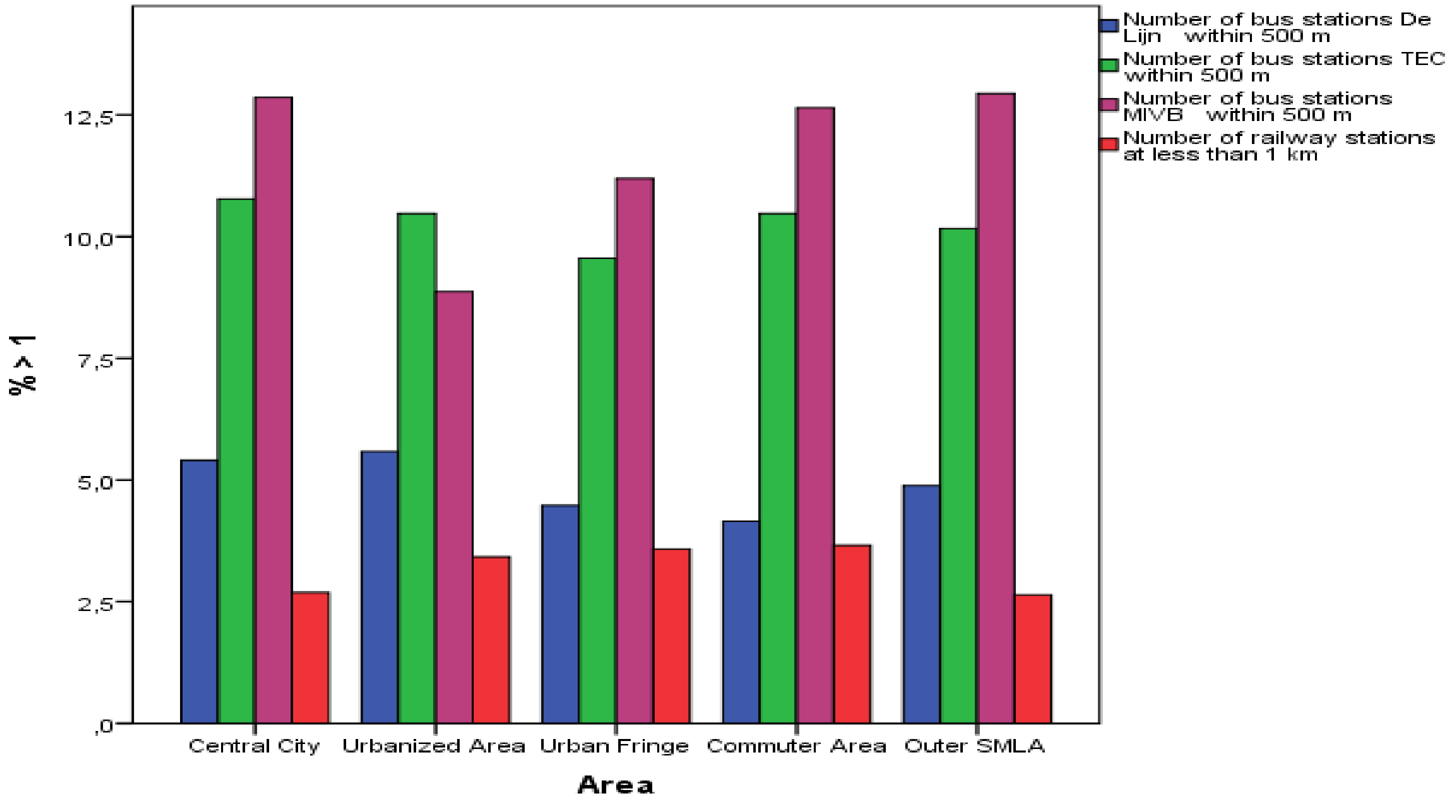


Figure 6_3A

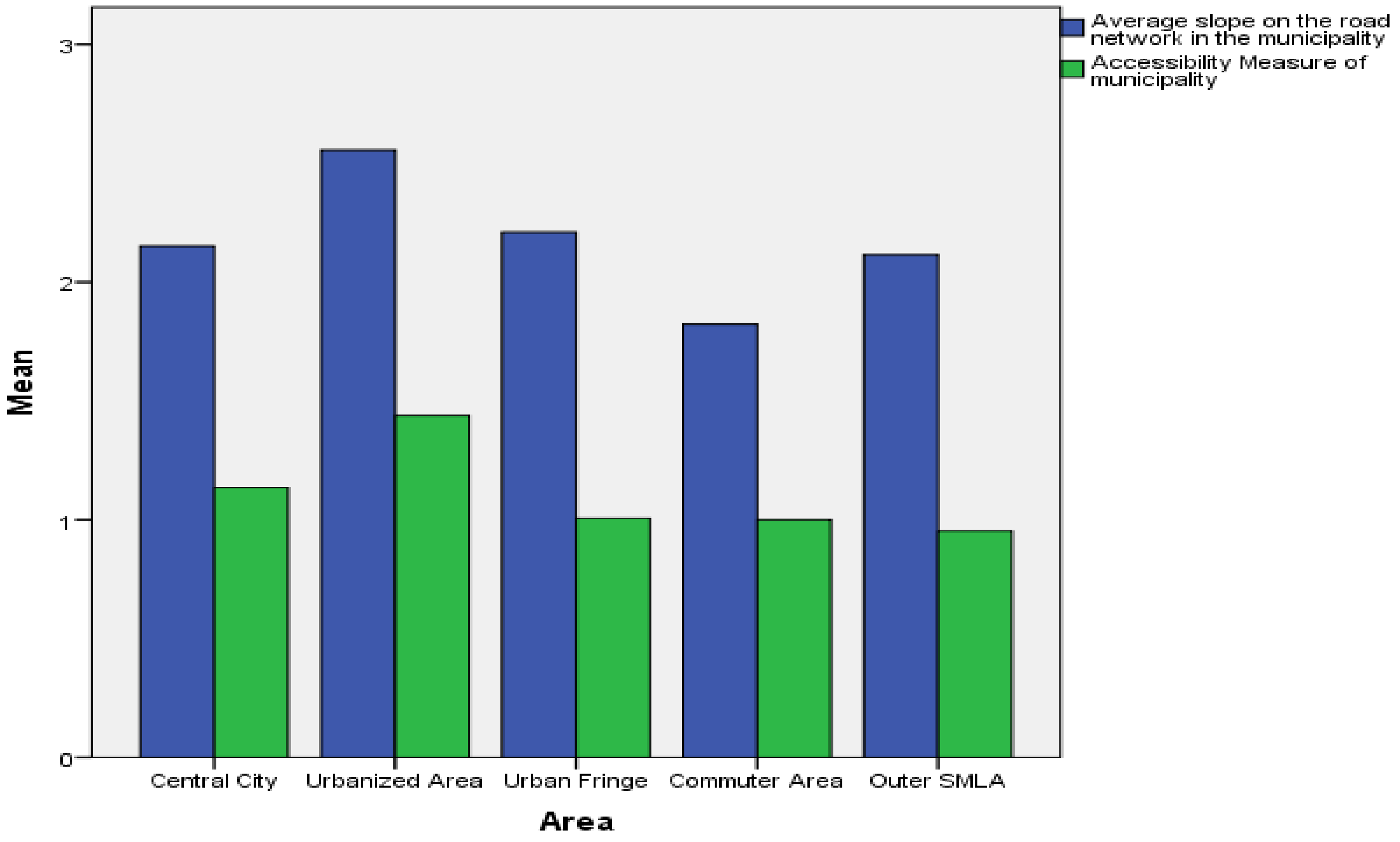


Table 1_3A

	In percentage terms (%)				
Mobility Management Measure	**Central City**	**Urbanized Area**	**Urban Fringe**	**Commuter Area**	**Outer SMLA**
Additional cycling Fee	44,8	41,3	42,5	41,1	41,5
Secured bicycle storage	29,5	28,3	28,8	30,4	26,5
Additional fee for work Trips with bike	7,6	6,3	7,3	7,2	7,3
Bicycles available for Home-to-Work travel	,8	,5	1,3	,5	1,3
Bicycles available at railway Station	,4	,9	,6	,9	,8
Bicycles available for work Trips	11,0	7,4	9,6	8,2	8,1
Provision of rain clothes	2,2	1,3	1,0	1,4	1,3
Improvement of infrastructure for bicycles	3,0	2,3	2,8	3,0	3,2
Covered bicycle storage	35,0	30,0	35,7	36,7	37,7
Changing room	23,0	22,8	23,3	23,6	24,4
Showers for bicycle users	24,3	23,5	25,4	22,5	25,0
Bicycle Repair Facilities	2,9	2,9	3,7	3,3	3,1
Bicycle Maintenance	2,0	,4	1,0	1,4	,7
Information on Cycling Routes	2,9	3,3	4,2	2,3	2,3
Bicycle other meausures	8,2	8,2	6,4	5,7	6,2
Organisation of a carpool	6,0	5,0	5,8	3,7	4,8
Linking to a central carpool database	7,2	3,1	4,2	2,3	3,0
Preferencial parking for carpool	1,8	2,7	2,1	1,4	1,6
Guaranteed ride home	1,4	1,7	1,5	1,2	1,9
Distribution of information carpool	5,4	3,1	4,2	3,2	4,0
Carpooling other measures	4,3	3,8	3,3	2,6	3,7
Public transport organized by employer	4,2	5,8	6,1	4,7	3,6
Supplementary allowance for public transport	28,3	23,3	19,6	20,8	19,8
Regular consultation by public transport company	7,0	3,4	5,7	3,2	4,2
Information on public transport	12,1	7,8	8,8	7,9	9,0
Encouraging public transport for work related trips	8,1	5,7	5,5	6,4	6,1
Public transport other meausres	9,9	10,6	7,2	5,8	8,4
Collaboration with enterprises	2,6	2,2	2,5	1,7	2,2
Information on SOV alternatives	8,0	6,1	6,0	4,2	5,2
Collaboration with mobility institutions	7,6	4,6	5,2	5,5	5,3
Regular Consultation with local authorities	8,8	7,6	9,7	8,1	7,1
Telework	7,8	5,7	4,8	4,2	4,8
Mobility coordinator	4,9	2,9	2,7	2,8	2,7
Parking charge	,8	,8	,3	,5	,7
Relocation of the site	,5	,7	,4	,6	,4
Relocation fee	,6	,9	,6	,1	,7
Regional or local financial measures	1,7	1,0	1,8	1,3	1,1
Diverse Other measures	8,9	7,8	5,4	4,7	5,6

Table 1_3A: Percentages of worksites that implement the corresponding measure in each area

Table 2_3A

	In percentage terms (%)				
Problems	**Central City**	**Urbanized Area**	**Urban Fringe**	**Commuter Area**	**Outer SMLA**
Dangerous traffic for car	16,4	14,7	13,1	12,5	12,3
Insufficient number of parking places	27,6	24,2	22,8	23,3	25,9
High parking costs for employer	5,1	5,2	3,9	4,0	3,6
Congestion	27,8	32,3	25,4	20,2	21,5
Other car problems	6,9	5,6	5,4	5,3	5,2
Dangerous traffic for bicycle	39,8	41,3	35,7	33,2	32,5
Unsafety (social)-bicycle	7,1	7,2	3,6	4,3	5,0
Company Image -bicycle	1,7	1,7	1,0	1,2	1,3
No possibilities for secured bicycle storage	10,7	11,9	9,3	8,0	10,6
No showers	22,0	17,2	14,6	16,3	17,2
Other bicycle problems	8,5	7,5	6,9	7,5	8,0
No or insufficient public transport service	24,0	26,0	28,7	25,1	27,9
Public transport service not adopted work hours	24,9	25,7	31,8	28,8	33,4
Public Transport Travel time	21,7	18,9	19,0	18,7	18,4
Low quality, safety and comfort	9,6	6,9	6,1	5,9	6,9
Distance to public transport stop	13,2	15,0	16,7	14,6	19,0
Feeling unsafe in the neighborhood	6,9	6,5	4,0	4,6	4,5
Other public transport problems	5,7	6,4	6,3	5,0	5,4
Recruiting problems due to bad accessibility	3,3	4,3	4,2	3,5	4,0
Cost for company cars	3,6	4,8	4,5	3,9	3,8
Cost of transport organized by the employer	3,4	3,5	4,3	3,9	2,9
Obligation to make a transport plan	3,4	2,4	2,4	1,7	2,1
Unsafe routes	8,5	7,4	7,5	6,9	6,7
Feeling insecure due to work hours	6,5	4,7	5,1	5,1	6,4
Protection of the environment	11,6	8,7	9,7	7,2	9,4
Health of employees	7,9	5,2	6,6	5,5	5,9
Positive collaboration between employer and employees	9,1	7,6	6,9	6,9	7,9
Equality among users of different modes	7,2	5,9	4,9	4,2	5,2
Other diverse problems	3,6	4,3	1,3	2,7	2,9

Table 2_3A: Percentages of worksites that has the corresponding problem in each area

5.1A. Modeling Process & Results

Component Matrix[a]

PCA Work Schedules	Component	
	1	2
FixedDummy	,843	,104
FlexDummy	-,658	,568
ShiftDummy	,457	,590
IrregularDummy	-,020	-,799

Extraction Method: Principal Component Analysis.
a. 2 components extracted.

Table 1_5A PCA Component matrices for Work Schedule

PCA for Bicycle	Component		
	1	2	3
BicyShower	,855	-,265	-,049
BicyChangeRoom	,858	-,253	-,002
BicyCoveredStorage	,736	-,132	,051
BicyBicycleMaintenance	,264	,610	-,284
BicyPossibilityRepairBicy	,411	,371	-,330
BicyBicycleforHTWT	,207	,557	-,209
BicyFee	,143	,397	,656
BicyFeeProfessionalTrips	,250	,217	,667

PCA for Carpool	Component
	1
Cporganisation	,722
CpcentralDatabse	,743
Cpinformation	,781

PCA for PT	Component
	1
PTdiscussionwithPTprovider	,842
Ptinformation	,842

Extraction Method: Principal Component Analysis.

Table 2_5A PCA Component matrices for Bike, Carpool and PT related measures

PCA for Diverse measures	Component
	1
DivInformationonSOValternatives	,759
DivDiscussionswithgovernments	,827
DivDiscussionwithLocalGovernment	,754

Extraction Method: Principal Component Analysis.

Table 3_5A PCA Component matrix for Diverse measures

Multinomial model with NLMIXED Procedure

Specifications	
Data Set	WORK.COMMUTING
Dependent Variable	Mode
Distribution for Dependent Variable	General
Replicate Variable	Weight
Optimization Technique	Dual Quasi-Newton
Integration Method	None

Dimensions	
Observations Used	24837
Observations Not Used	0
Total Observations	24837
Parameters	106

Table 4_5A: MNL model specification

Parameter Estimates					
Parameter; Carpool	Estimate	Standard Error	DF	t Value	Pr>|t|
alpha2	-3.9684	0.06915	2,5E+04	-57.39	<.0001
b_LogSize2	0.5680	0.01705	2,5E+04	33.32	<.0001
b_FFixedSchedule2	0.01922	0.007091	2,5E+04	2.71	0.0067
b_FRegularShiftSchedule2	0.2101	0.007937	2,5E+04	26.48	<.0001
b_CPguaranteedRideHome2	0.2359	0.04359	2,5E+04	5.41	<.0001
b_DummyABC2	-0.3257	0.1190	2,5E+04	-2.74	0.0062
b_DummyD2	0.02137	0.05388	2,5E+04	0.40	0.6917
b_DummyE2	0.1716	0.06641	2,5E+04	2.58	0.0097
b_DummyF2	0.9649	0.06104	2,5E+04	15.81	<.0001
b_DummyG2	-0.6413	0.05776	2,5E+04	-11.10	<.0001
b_DummyH2	-0.1553	0.09180	2,5E+04	-1.69	0.0907
b_DummyI2	0.06341	0.05617	2,5E+04	1.13	0.2590
b_DummyJ2	-0.3400	0.07132	2,5E+04	-4.77	<.0001
b_DummyK2	-0.4051	0.05933	2,5E+04	-6.83	<.0001
b_DummyL2	0.3789	0.1340	2,5E+04	2.83	0.0047
b_DummyM2	-0.6366	0.08211	2,5E+04	-7.75	<.0001
b_DummyN2	-0.6656	0.06749	2,5E+04	-9.86	<.0001
b_DummyZ2	-0.3387	0.05319	2,5E+04	-6.37	<.0001
b_Core2	0.2396	0.02546	2,5E+04	9.41	<.0001
b_Agglomeration2	0.1705	0.02896	2,5E+04	5.89	<.0001
b_Forenszone2	0.2306	0.02810	2,5E+04	8.21	<.0001
b_outsideAgglomeration2	0.2575	0.02611	2,5E+04	9.86	<.0001
b_Cporganisation2	0.1559	0.02906	2,5E+04	5.37	<.0001

b_CPcentralDatabase2	0.1999	0.03363	2,5E+04	5.94	<.0001
b_Cpinformation2	-0.3439	0.03690	2,5E+04	-9.32	<.0001
b_ProbCarCONGESTION2	0.2215	0.01444	2,5E+04	15.34	<.0001
b_DTrainstationwithin1km2	-0.04982	0.01440	2,5E+04	-3.46	0.0005

Table 5_5A: MNL Parameter Estimates; Carpool

Parameter; Train	Estimate	Standard Error	DF	t Value	Pr > |t|
alpha3	-5.1264	0.06685	2,5E+04	-76.69	<.0001
b_LogSize3	0.3973	0.01213	2,5E+04	32.75	<.0001
b_FFixedSchedule3	-0.3079	0.004791	2,5E+04	-64.26	<.0001
b_ProbCarCONGESTION3	0.1699	0.01066	2,5E+04	15.94	<.0001
b_ProbCarParkingCostEmployer3	0.1687	0.02120	2,5E+04	7.96	<.0001
b_DTrainstationwithin1km3	1.0547	0.01039	2,5E+04	101.46	<.0001
b_DummyABC3	-1.3815	0.3221	2,5E+04	-4.29	<.0001
b_DummyD3	-1.0428	0.06141	2,5E+04	-16.98	<.0001
b_DummyE3	-0.2400	0.07242	2,5E+04	-3.31	0.0009
b_DummyF3	-1.0021	0.1014	2,5E+04	-9.88	<.0001
b_DummyG3	-0.8658	0.06074	2,5E+04	-14.25	<.0001
b_DummyH3	0.1722	0.07410	2,5E+04	2.32	0.0202
b_DummyI3	0.5861	0.05820	2,5E+04	10.07	<.0001
b_DummyJ3	0.7859	0.05929	2,5E+04	13.26	<.0001
b_DummyK3	0.6678	0.05782	2,5E+04	11.55	<.0001
b_DummyL3	1.6016	0.08335	2,5E+04	19.21	<.0001
b_DummyM3	0.5193	0.06488	2,5E+04	8.00	<.0001
b_DummyN3	-0.2500	0.06671	2,5E+04	-3.75	0.0002
b_DummyZ3	0.5807	0.05628	2,5E+04	10.32	<.0001
b_Core3	1.3933	0.02853	2,5E+04	48.84	<.0001
b_Agglomeration3	1.3708	0.02940	2,5E+04	46.62	<.0001
b_Forenszone3	0.1560	0.03411	2,5E+04	4.57	<.0001
b_outsideAgglomeration3	-0.00221	0.03299	2,5E+04	-0.07	0.9466
b_AccessibilityMunicipality3	-0.2990	0.02305	2,5E+04	-12.97	<.0001

Table 6_5A: MNL Parameter Estimates; Train

Parameter; MTB	Estimate	Standard Error	DF	t Value	Pr > |t|
alpha4	-4.4675	0.06465	2,5E+04	-69.11	<.0001
b_LogSize4	0.06811	0.01374	2,5E+04	4.96	<.0001
b_FFixedSchedule4	-0.06253	0.005246	2,5E+04	-11.92	<.0001
b_FRegularShiftSchedule4	-0.02597	0.005999	2,5E+04	-4.33	<.0001
b_FPTInfo4	0.02844	0.004940	2,5E+04	5.76	<.0001
b_PTorganisedEmployer4	0.1477	0.02526	2,5E+04	5.85	<.0001
b_PTextrafee4	0.02416	0.01208	2,5E+04	2.00	0.0455
b_ProbPTtraveltime4	-0.1192	0.01351	2,5E+04	-8.82	<.0001
b_ProbPTunsafeenvironment4	0.2849	0.01974	2,5E+04	14.43	<.0001
b_NBusStopswithin500m4	0.06846	0.003729	2,5E+04	18.36	<.0001

b_DBusStopwithin500m4	0.9862	0.03158	2,5E+04	31.22	<.0001
b_DummyABC4	-1.2420	0.2425	2,5E+04	-5.12	<.0001
b_DummyD4	-1.3230	0.05268	2,5E+04	-25.11	<.0001
b_DummyE4	-1.2778	0.07503	2,5E+04	-17.03	<.0001
b_DummyF4	-1.4447	0.09365	2,5E+04	-15.43	<.0001
b_DummyG4	-0.2652	0.04809	2,5E+04	-5.51	<.0001
b_DummyH4	1.1055	0.05449	2,5E+04	20.29	<.0001
b_DummyI4	-0.7581	0.05202	2,5E+04	-14.57	<.0001
b_DummyJ4	-0.06667	0.05335	2,5E+04	-1.25	0.2114
b_DummyK4	-0.5420	0.05069	2,5E+04	-10.69	<.0001
b_DummyL4	0.4145	0.1032	2,5E+04	4.01	<.0001
b_DummyM4	-0.5296	0.06316	2,5E+04	-8.39	<.0001
b_DummyN4	0.2386	0.05209	2,5E+04	4.58	<.0001
b_DummyZ4	0.1911	0.04622	2,5E+04	4.13	<.0001
b_Core4	1.3344	0.02744	2,5E+04	48.64	<.0001
b_Agglomeration4	1.4428	0.02815	2,5E+04	51.25	<.0001
b_Forenszone4	-0.4032	0.03717	2,5E+04	-10.85	<.0001
b_outsideAgglomeration4	-0.4425	0.03445	2,5E+04	-12.84	<.0001

Table 7_5A: MNL Parameter Estimates; MTB

Parameter; Bike	Estimate	Standard Error	DF	t Value	Pr > |t|
alpha5	-1.3609	0.05634	2,5E+04	-24.15	<.0001
b_LogSize5	-0.06063	0.01240	2,5E+04	-4.89	<.0001
b_FFixedSchedule5	0.04520	0.004529	2,5E+04	9.98	<.0001
b_FBikeFacilities5	-0.00300	0.004340	2,5E+04	-0.69	0.4894
b_FBikeProvision5	0.03322	0.003456	2,5E+04	9.61	<.0001
b_FCyclingFee5	0.03605	0.004303	2,5E+04	8.38	<.0001
b_ProbBicyDangerousTraffic5	-0.07038	0.009290	2,5E+04	-7.58	<.0001
b_ProbBicySocialInsecurity5	-0.1035	0.02076	2,5E+04	-4.99	<.0001
b_DummyABC5	0.1032	0.09297	2,5E+04	1.11	0.2670
b_DummyD5	0.03140	0.04572	2,5E+04	0.69	0.4923
b_DummyE5	-0.3958	0.06821	2,5E+04	-5.80	<.0001
b_DummyF5	-0.6663	0.07190	2,5E+04	-9.27	<.0001
b_DummyG5	-0.1050	0.04690	2,5E+04	-2.24	0.0251
b_DummyH5	0.2186	0.06758	2,5E+04	3.23	0.0012
b_DummyI5	0.3760	0.04667	2,5E+04	8.06	<.0001
b_DummyJ5	-0.4120	0.06620	2,5E+04	-6.22	<.0001
b_DummyK5	-0.3448	0.05141	2,5E+04	-6.71	<.0001
b_DummyL5	0.4414	0.1220	2,5E+04	3.62	0.0003
b_DummyM5	0.7184	0.05185	2,5E+04	13.85	<.0001
b_DummyN5	0.09762	0.05310	2,5E+04	1.84	0.0660
b_DummyZ5	0.8391	0.04446	2,5E+04	18.87	<.0001
b_Core5	0.1796	0.01568	2,5E+04	11.45	<.0001
b_Agglomeration5	-0.04756	0.02108	2,5E+04	-2.26	0.0240

b_Forenszone5	0.08216	0.01747	2,5E+04	4.70	<.0001
b_outsideAgglomeration5	0.1788	0.01629	2,5E+04	10.97	<.0001
b_LogSlopeMunicipality5	-3.1230	0.02275	2,5E+04	-137.25	<.0001
b_AccessibilityMunicipality5	-0.5438	0.02199	2,5E+04	-24.73	<.0001

Table 8_5A: MNL Parameter Estimates; Bike

Multinomial model with Random effects with PROC NL Mixed

Specifications	
Data Set	WORK.FINAL
Dependent Variable	Mode
Distribution for Dependent Variable	General
Random Effects	u2 u3 u4 u5
Distribution for Random Effects	Normal
Subject Variable	Arrondissement
Replicate Variable	Weight
Optimization Technique	Dual Quasi-Newton
Integration Method	Adaptive Gaussian Quadrature

Dimensions	
Observations Used	24837
Observations Not Used	0
Total Observations	24837
Subjects	3699
Max Obs Per Subject	7224
Parameters	55
Quadrature Points	1

Table 9_5A: MNL model with random effects

Parameter; Carpool	Estimate	Standard Error	DF	t Value	Pr > |t|	Alpha
alpha2	-1.0571	0.04061	3695	-26.03	<.0001	0.05
b_FixedDummy2	0.1150	0.01115	3695	10.31	<.0001	0.05
b_FRegularShiftSchedule2	0.2867	0.004791	3695	59.85	<.0001	0.05
b_CPguaranteedRideHome2	0.1750	0.03148	3695	5.56	<.0001	0.05
b_Core2	0.1229	0.01824	3695	6.74	<.0001	0.05
b_Agglomeration2	0.07974	0.02067	3695	3.86	0.0001	0.05
b_Forenszone2	0.1203	0.02176	3695	5.53	<.0001	0.05
b_outsideAgglomeration2	0.1056	0.01958	3695	5.39	<.0001	0.05
b_Cporganisation2	0.1690	0.01864	3695	9.07	<.0001	0.05
b_ProbCarCONGESTION2	0.02231	0.01022	3695	2.18	0.0291	0.05
b_DTrainstationwithin1km2	-0.07117	0.009286	3695	-7.66	<.0001	0.05

Parameter; Train	Estimate	Standard Error	DF	t Value	Pr > |t|	Alpha
alpha3	-1.5904	0.02598	3695	-61.22	<.0001	0.05
b_FixedDummy3	-0.06529	0.009646	3695	-6.77	<.0001	0.05
b_ProbCarCONGESTION3	0.03519	0.01001	3695	-3.52	0.0004	0.05
b_ProbCarParkingCostEmployer3	0.04005	0.01961	3695	2.04	0.0412	0.05
b_DTrainstationwithin1km3	0.5613	0.008479	3695	66.20	<.0001	0.05
b_Core3	0.8950	0.02125	3695	42.12	<.0001	0.05
b_Agglomeration3	0.3057	0.02398	3695	12.75	<.0001	0.05
b_Forenszone3	0.4332	0.02494	3695	17.37	<.0001	0.05
b_outsideAgglomeration3	0.2640	0.02499	3695	10.56	<.0001	0.05
b_AccessibilityMunicipality3	-0.00969	0.03660	3695	-0.26	0.7912	0.05

Parameter; MTB	Estimate	Standard Error	DF	t Value	Pr > |t|	Alpha
alpha4	-1.3005	0.02319	3695	-56.09	<.0001	0.05
b_FixedDummy4	-0.04205	0.009564	3695	-4.40	<.0001	0.05
b_FRegularShiftSchedule4	-0.06463	0.004219	3695	-15.32	<.0001	0.05
b_FPTInfo4	-0.01599	0.004087	3695	-3.91	<.0001	0.05
b_PTextrafee4	0.1115	0.008931	3695	12.48	<.0001	0.05
b_ProbPTtraveltime4	0.01933	0.009653	3695	2.00	0.0453	0.05
b_DBusStopwithin500m4	0.5942	0.01518	3695	39.13	<.0001	0.05
b_Core4	0.4207	0.01678	3695	25.07	<.0001	0.05
b_Agglomeration4	0.2388	0.01889	3695	12.64	<.0001	0.05
b_Forenszone4	-0.09096	0.02109	3695	-4.31	<.0001	0.05
b_outsideAgglomeration4	-0.4242	0.02025	3695	-20.95	<.0001	0.05

Parameter; Bike	Estimate	Standard Error	DF	t Value	Pr > |t|	Alpha
alpha5	0.5155	0.04442	3695	11.61	<.0001	0.05
b_FixedDummy5	0.1027	0.008670	3695	11.85	<.0001	0.05
b_FBikeProvision5	0.02885	0.003287	3695	8.78	<.0001	0.05
b_BicyFee5	0.04054	0.007179	3695	5.65	<.0001	0.05
b_ProbBicyDangerousTraffic5	0.005695	0.007544	3695	0.75	0.4504	0.05
b_ProbBicySocialInsecurity5	0.01570	0.01604	3695	0.98	0.3278	0.05
b_Core5	0.3642	0.02216	3695	16.44	<.0001	0.05
b_Agglomeration5	-0.1106	0.01857	3695	-5.96	<.0001	0.05
b_Forenszone5	0.1117	0.01818	3695	6.15	<.0001	0.05
b_outsideAgglomeration5	0.07998	0.01718	3695	4.66	<.0001	0.05
b_slopeMunicipality5	-0.2011	0.003963	3695	-50.74	<.0001	0.05
b_AccessibilityMunicipality5	0.08671	0.03027	3695	2.86	0.0042	0.05
b_LogJobDensityMunicipality20055	-0.1996	0.01021	3695	-19.54	<.0001	0.05

Cholesky-root reparameterization of covariance matrix	Estimate	Standard Error	DF	t Value	Pr > |t|	Alpha
t2	-0.07647	0.008516	3695	-8.98	<.0001	0.05
t3	0.1550	0.02727	3695	5.68	<.0001	0.05
t4	-0.1237	0.007369	3695	-16.78	<.0001	0.05
t5	0.1001	0.01488	3695	6.73	<.0001	0.05
t23	0.2909	0.02037	3695	14.28	<.0001	0.05
t24	0.04272	0.01388	3695	3.08	0.0021	0.05
t25	0.006525	0.01393	3695	0.47	0.6394	0.05
t34	0.05668	0.01971	3695	2.88	0.0040	0.05
t35	-0.06001	0.01987	3695	-3.02	0.0025	0.05
t45	0.02075	0.01383	3695	1.50	0.1337	0.05

Table 10_5A: Parameter Estimates of MNL model with random effects

Additional Estimates								
Label	Estimate	Standard Error	DF	t Value	Pr > |t|	Alpha	Lower	Upper
Var2	0.005848	0.001302	3695	4.49	<.0001	0.05	0.003294	0.008401
Var3	0.1086	0.009814	3695	11.07	<.0001	0.05	0.08940	0.1279
Var4	0.02033	0.002105	3695	9.66	<.0001	0.05	0.01620	0.02445
Var5	0.01409	0.001911	3695	7.37	<.0001	0.05	0.01034	0.01784
cov32	-0.02224	0.002870	3695	-7.75	<.0001	0.05	-0.02787	-0.01662
cov42	-0.00327	0.001061	3695	-3.08	0.0021	0.05	-0.00535	-0.00119
cov43	0.02121	0.003836	3695	5.53	<.0001	0.05	0.01369	0.02873
cov52	-0.00050	0.001044	3695	-0.48	0.6327	0.05	-0.00255	0.001548
cov53	-0.00740	0.002971	3695	-2.49	0.0127	0.05	-0.01323	-0.00158
cov54	-0.00569	0.001233	3695	-4.62	<.0001	0.05	-0.00811	-0.00327

Table 11_5A: Parameter Estimates for covariance matrix of random effects

Parameter Estimates of random effects for Carpool							
Borough	Effect	Estimate	Probt	Borough	Effect	Estimate	Probt
Maas	u2	0.14674	0.01804	Bru	u2	-0.03261	0.39157
Genk	u2	0.14010	0.00472	Aar	u2	-0.03145	0.58607
Leuv	u2	-0.09994	0.00780	Chim	u2	0.02933	0.69024
Overp	u2	0.09294	0.12532	Cin	u2	-0.02834	0.67387
Ath	u2	-0.08600	0.14325	Mous	u2	0.02779	0.59870
Turn	u2	0.08526	0.07777	Virt	u2	0.02654	0.69086
Brug	u2	-0.08244	0.02671	Tour	u2	0.02332	0.60696
Gent	u2	-0.07785	0.01464	Lieg	u2	0.02091	0.53117
Char	u2	0.07427	0.07000	Antw	u2	-0.01884	0.49146
Libra	u2	-0.06983	0.21182	Viels	u2	0.01769	0.80482
Oud	u2	-0.05838	0.29794	Zinnik	u2	0.01725	0.72486

Mons	u2	0.05742	0.17822	Truid	u2	0.01686	0.76521
Bast	u2	0.05638	0.41556	Oost	u2	0.01665	0.71652
Tien	u2	-0.05444	0.31972	Couv	u2	0.01662	0.81671
Malm	u2	0.05424	0.41342	Iep	u2	-0.01464	0.75772
Has	u2	0.04990	0.18482	Mech	u2	0.01440	0.71374
Tong	u2	0.04944	0.40839	Rons	u2	0.01435	0.81812
Huy	u2	-0.04773	0.41538	SVith	u2	0.01294	0.86164
Eup	u2	0.03897	0.52131	Mol	u2	-0.00742	0.89013
March	u2	-0.03855	0.55177	Arl	u2	0.00346	0.94523
Verv	u2	0.03707	0.44046	Nam	u2	-0.00271	0.94206
Roes	u2	-0.03565	0.41545	Beaur	u2	0.00131	0.98418
Veur	u2	-0.03446	0.49571	Kort	u2	0.00073	0.98350
Diest	u2	0.03399	0.53642				

Table 12_5A: Parameter estimates of random effects for each borough; Carpool

Parameter Estimates of random effects for Train

Borough	Effect	Estimate	Probt	Borough	Effect	Estimate	Probt
Maas	u3	-0.73142	0.00259	Chim	u3	-0.14387	0.64603
Genk	u3	-0.69667	0.00003	Arl	u3	0.12368	0.48218
Bru	u3	0.54569	0.00000	Mous	u3	-0.11300	0.56316
Overp	u3	-0.46511	0.05238	Rons	u3	-0.11127	0.65562
Turn	u3	-0.45747	0.00588	Virt	u3	-0.10897	0.69314
Ath	u3	0.39037	0.07927	Aar	u3	0.09577	0.66597
Libra	u3	0.36992	0.07590	Verv	u3	-0.09224	0.57759
Brug	u3	0.30110	0.00070	SVith	u3	-0.08960	0.77769
Malm	u3	-0.28470	0.29687	Nam	u3	0.08783	0.35922
Oud	u3	0.26798	0.20785	Viels	u3	-0.07653	0.80070
Gent	u3	0.26675	0.00001	Zinnik	u3	0.07087	0.66795
Leuv	u3	0.24947	0.00282	Couv	u3	-0.06704	0.82504
Has	u3	-0.23643	0.02625	Iep	u3	0.06522	0.69141
Huy	u3	0.23505	0.30545	Kort	u3	-0.05909	0.49878
Tien	u3	0.23441	0.25001	Char	u3	-0.04986	0.62010
Bast	u3	-0.23184	0.42315	Antw	u3	0.04489	0.33796
Diest	u3	-0.21667	0.29754	Lieg	u3	-0.03802	0.62916
Tong	u3	-0.21588	0.35767	Oost	u3	-0.03583	0.81198
March	u3	0.19540	0.45903	Mol	u3	0.03314	0.86879
Eup	u3	-0.19186	0.42908	Tour	u3	-0.02976	0.83780
Veur	u3	0.17376	0.33686	Mons	u3	-0.01770	0.88040
Truid	u3	-0.16668	0.43944	Beaur	u3	0.01040	0.96936
Cin	u3	0.15544	0.57605	Mech	u3	0.00420	0.96983
Roes	u3	0.15375	0.27869				

Table 13_5A: Parameter estimates of random effects for each borough; Train

Parameter Estimates of random effects for MTB							
Borough	Effect	Estimate	Probt	Borough	Effect	Estimate	Probt
Zinnik	u4	0.27129	0.01233	Malm	u4	-0.03045	0.81792
Kort	u4	-0.26597	0.00058	Veur	u4	0.03044	0.78971
Genk	u4	-0.20955	0.03879	Ath	u4	-0.03042	0.81000
Arl	u4	0.20458	0.07242	Nam	u4	-0.02923	0.71881
Turn	u4	-0.18874	0.06676	Mech	u4	0.02624	0.75642
Bru	u4	0.17490	0.00000	Leuv	u4	-0.02451	0.73953
Maas	u4	-0.14053	0.24751	Mous	u4	-0.02058	0.86013
Antw	u4	0.14033	0.00055	Mol	u4	0.02050	0.86320
Tour	u4	-0.13034	0.20389	Brug	u4	-0.01809	0.81857
Overp	u4	-0.09364	0.45133	Mons	u4	-0.01762	0.84200
Huy	u4	0.09056	0.47594	Gent	u4	0.01605	0.77772
Lieg	u4	0.08861	0.15639	Aar	u4	-0.01569	0.89923
Libra	u4	0.06922	0.57879	Diest	u4	0.01336	0.91017
Tien	u4	0.06295	0.59993	Beaur	u4	0.01172	0.93022
Oost	u4	0.05717	0.57011	Has	u4	-0.01130	0.88575
Oud	u4	0.05638	0.64766	Iep	u4	0.01029	0.92591
Truid	u4	-0.05280	0.66329	Cin	u4	0.00810	0.95219
Char	u4	0.05204	0.50573	Viels	u4	-0.00558	0.96786
Chim	u4	-0.04507	0.74709	Eup	u4	-0.00301	0.98101
March	u4	0.04238	0.75022	Virt	u4	-0.00170	0.98985
SVith	u4	-0.03919	0.78036	Couv	u4	0.00167	0.99040
Tong	u4	0.03501	0.77858	Bast	u4	0.00124	0.99269
Verv	u4	0.03219	0.76487	Roes	u4	0.00041	0.99684
Rons	u4	-0.03088	0.80950				

Table 14_5A: Parameter estimates of random effects for each borough; MTB

Parameter Estimates of random effects for bike							
Borough	Effect	Estimate	Probt	Borough	Effect	Estimate	Probt
Char	u5	-0.36827	0.00001	Gent	u5	0.03527	0.46505
Mons	u5	-0.25195	0.00230	Cin	u5	-0.03088	0.78691
Leuv	u5	0.24508	0.00025	Bast	u5	-0.03085	0.78680
Zinnik	u5	-0.16047	0.09086	Bru	u5	-0.02946	0.42697
Arl	u5	-0.14880	0.14556	March	u5	-0.02874	0.80041
Truid	u5	0.10604	0.29026	Brug	u5	0.02784	0.66851
Kort	u5	0.08911	0.12073	Has	u5	0.02380	0.71414
Genk	u5	0.08901	0.27982	Tien	u5	0.02225	0.82826
Diest	u5	0.08175	0.40116	Roes	u5	0.01743	0.83188
Lieg	u5	-0.08084	0.23030	Eup	u5	0.01658	0.87667
Maas	u5	0.07506	0.44028	Mous	u5	0.01653	0.86359
Libra	u5	-0.07304	0.50025	Huy	u5	-0.01612	0.88453
Antw	u5	0.06907	0.05155	Iep	u5	0.01536	0.86233
Turn	u5	0.06835	0.41803	Veur	u5	-0.01294	0.88821
Rons	u5	0.06694	0.53615	Chim	u5	0.01199	0.91830

Verv	u5	-0.06597	0.51820	Couv	u5	-0.01130	0.92283
Tour	u5	-0.06509	0.45816	Beaur	u5	-0.01024	0.92817
Aar	u5	0.05708	0.58951	Oud	u5	0.00857	0.93356
Mech	u5	-0.05660	0.44770	Tong	u5	0.00655	0.94953
Nam	u5	-0.05488	0.50466	Mol	u5	0.00634	0.94791
Malm	u5	0.05214	0.64607	Virt	u5	-0.00605	0.95778
Oost	u5	-0.05037	0.56462	Ath	u5	0.00078	0.99422
Overp	u5	0.04711	0.63524	Viels	u5	-0.00071	0.99517
SVith	u5	0.03627	0.75791				

Table 15_5A: Parameter estimates of random effects for each borough; bike

5.2A SAS commands

5.2.1A SAS command for MNL

```
proc nlmixed data=Final METHOD=GAUSS GCONV=0 MINITER=3 G4=120;

parms  alpha2=-3.96 b_LogSize2=0.56 b_FFixedSchedule2=0.019 b_FRegularFlexShiftSchedule2=0.21
b_CPguaranteedRideHome2=0.23 b_DummyABC2=-0.32 b_DummyD2=-0.021 b_DummyE2=0.17 b_DummyF2=0.96
b_DummyG2=-0.64 b_DummyH2=-0.15 b_DummyI2=0.06 b_DummyJ2=-0.33 b_DummyK2=-0.40  b_DummyL2=0.37
b_DummyM2=-0.63    b_DummyN2=-0.66    b_DummyZ2=-0.33    b_Core2=0.23    b_Agglomeration2=0.17
b_Forenszone2=0.23             b_outsideAgglomeration2=0.26             b_Cporganisation2=0.15
b_CPcentralDatabase2=0.19           b_Cpinformation2=-0.34           b_ProbCarCONGESTION2=0.22
b_DTrainstationwithin1km2=-0.04

alpha3=-5.12       b_LogSize3=0.39       b_FFixedSchedule3=-0.30       b_ProbCarCONGESTION3=0.16
b_ProbCarParkingCostEmployer3=0.17        b_DTrainstationwithin1km3=1.05        b_DummyABC3=-1.37
b_DummyD3=-1.05 b_DummyE3=-0.25 b_DummyF3=-1.01 b_DummyG3=-0.87 b_DummyH3=0.17 b_DummyI3=0.58
b_DummyJ3=0.78  b_DummyK3=0.66  b_DummyL3=1.6  b_DummyM3=0.51  b_DummyN3=-0.24  b_DummyZ3=0.58
b_Core3=1.39     b_Agglomeration3=1.37      b_Forenszone3=0.15      b_outsideAgglomeration3=0.01
b_AccessibilityMunicipality3=-0.27

alpha4=-4.46   b_LogSize4=0.06   b_FFixedSchedule4=-0.06   b_FRegularFlexShiftSchedule4=-0.025
b_FPTInfo4=0.028   b_PTorganisedEmployer4=0.14   b_PTextrafee4=0.02   b_ProbPTtraveltime4=-0.11
b_ProbPTunsafeenvironment4=-0.06      b_NBusStopswithin500m4=0.07      b_DBusStopwithin500m4=0.99
b_DummyABC4=-1.24      b_DummyD4=-1.33      b_DummyE4=-1.27      b_DummyF4=-1.44      b_DummyG4=-0.26
b_DummyH4=1.10 b_DummyI4=-0.75 b_DummyJ4=-0.06 b_DummyK4=-0.54 b_DummyL4=0.41 b_DummyM4=-0.52
b_DummyN4=0.23    b_DummyZ4=0.19    b_Core4=1.33    b_Agglomeration4=1.44    b_Forenszone4=-0.40
b_outsideAgglomeration4=-0.44

alpha5=-2.36       b_LogSize5=-0.06       b_FFixedSchedule5=0.04       b_FBikeFacilities5=0.038
b_FBikeProvision5=0.036           b_FCyclingFee5=0.03           b_ProbBicyDangerousTraffic5=-0.07
b_ProbBicySocialInsecurity5=-0.10 b_DummyABC5=0.031 b_DummyD5=0.03 b_DummyE5=-0.39 b_DummyF5=-
0.66    b_DummyG5=-0.10    b_DummyH5=0.21    b_DummyI5=0.37    b_DummyJ5=-0.41    b_DummyK5=-0.34
b_DummyL5=0.44 b_DummyM5=0.71 b_DummyN5=-0.09 b_DummyZ5=0.83 b_Core5=0.17 b_Agglomeration5=-
0.04     b_Forenszone5=0.08     b_outsideAgglomeration5=0.17     b_LogSlopeMunicipality5=-3.12
b_AccessibilityMunicipality5=-0.54 ;

Utility2=alpha2+b_LogSize2*LogSize+b_FFixedSchedule2*FFixedSchedule+b_FRegularFlexShiftSchedul
e2*FRegularFlexShiftSchedule+b_CPguaranteedRideHome2*CPguaranteedRideHome+b_Cporganisation2*Cp
organisation+b_CPcentralDatabase2*CPcentralDatabase+b_Cpinformation2*Cpinformation+b_DummyABC2
*DummyABC  +  b_DummyD2*DummyD  +  b_DummyE2*DummyE  +  b_DummyF2*DummyF  +  b_DummyG2*DummyG  +
b_DummyH2*DummyH + b_DummyI2*DummyI + b_DummyJ2*DummyJ + b_DummyK2*DummyK + b_DummyL2*DummyL +
b_DummyM2*DummyM      +      b_DummyN2*DummyN      +      b_DummyZ2*DummyZ      +      b_Core2*Core     +
b_Agglomeration2*Agglomeration+b_Forenszone2*Forenszone+b_outsideAgglomeration2*outsideAgglome
ration+b_ProbCarCONGESTION2*ProbCarCONGESTION+b_DTrainstationwithin1km2*DTrainstationwithin1km
+ b_AccessibilityMunicipality3*AccessibilityMunicipality;



Utility3=alpha3+b_LogSize3*LogSize+b_FFixedSchedule3*FFixedSchedule+b_ProbCarCONGESTION3*ProbC
arCONGESTION+b_ProbCarParkingCostEmployer3*ProbCarParkingCostEmployer+b_DTrainstationwithin1km
3*DTrainstationwithin1km   +   b_DummyABC3*DummyABC   +   b_DummyD3*DummyD   +   b_DummyE3*DummyE   +
b_DummyF3*DummyF + b_DummyG3*DummyG + b_DummyH3*DummyH + b_DummyI3*DummyI + b_DummyJ3*DummyJ +
b_DummyK3*DummyK + b_DummyL3*DummyL + b_DummyM3*DummyM + b_DummyN3*DummyN + b_DummyZ3*DummyZ +
b_Core3*Core+b_Agglomeration3*Agglomeration+b_Forenszone3*Forenszone+b_outsideAgglomeration3*o
utsideAgglomeration;



Utility4=alpha4+b_LogSize4*LogSize+b_FFixedSchedule4*FFixedSchedule+b_FRegularFlexShiftSchedul
e4*FRegularFlexShiftSchedule + b_FPTInfo4*FPTInfo + b_PTorganisedEmployer4*PTorganisedEmployer
+b_PTextrafee4*PTextrafee+b_ProbPTtraveltime4*ProbPTtraveltime+b_ProbPTunsafeenvironment4*Prob
PTunsafeenvironment+b_NBusStopswithin500m4*NBusStopswithin500m+b_DBusStopwithin500m4*DBusStopw
ithin500m+ b_DummyABC4*DummyABC + b_DummyD4*DummyD +  b_DummyE4*DummyE + b_DummyF4*DummyF +
```

```
b_DummyG4*DummyG + b_DummyH4*DummyH + b_DummyI4*DummyI + b_DummyJ4*DummyJ + b_DummyK4*DummyK +
b_DummyL4*DummyL + b_DummyM4*DummyM + b_DummyN4*DummyN + b_DummyZ4*DummyZ + b_Core4*Core +
b_Agglomeration4*Agglomeration+b_Forenszone4*Forenszone+b_outsideAgglomeration4*outsideAgglome
ration;


Utility5=alpha5+b_LogSize5*LogSize+b_FFixedSchedule5*FFixedSchedule+b_FBikeFacilities5*FBikeFa
cilities+b_FBikeProvision5*FBikeProvision+b_FCyclingFee5*FCyclingFee+b_ProbBicyDangerousTraffi
c5*ProbBicyDangerousTraffic+b_ProbBicySocialInsecurity5*ProbBicySocialInsecurity+b_DummyABC5*D
ummyABC+b_DummyD5*DummyD+b_DummyE5*DummyE+b_DummyF5*DummyF+b_DummyG5*DummyG+b_DummyH5*DummyH +
b_DummyI5*DummyI + b_DummyJ5*DummyJ + b_DummyK5*DummyK + b_DummyL5*DummyL + b_DummyM5*DummyM +
b_DummyN5*DummyN + b_DummyZ5*DummyZ + b_Core5*Core + b_Agglomeration5*Agglomeration +
b_Forenszone5*Forenszone+b_outsideAgglomeration5*outsideAgglomeration+b_LogSlopeMunicipality5*
LogSlopeMunicipality + b_AccessibilityMunicipality5*AccessibilityMunicipality;


exp_utility2=exp(utility2);

exp_utility3=exp(utility3);

exp_utility4=exp(utility4);

exp_utility5=exp(utility5);

sum= 1 + exp_utility2 + exp_utility3 + exp_utility4 + exp_utility5;


if mode=1 then p_mode = 1/sum;

if mode=2 then p_mode = exp_utility2/sum;

if mode=3 then p_mode = exp_utility3/sum;

if mode=4 then p_mode = exp_utility4/sum;

if mode=5 then p_mode = exp_utility5/sum;


if p_mode>1e-8 then ll=log(p_mode);

 else ll=-1e10;


model mode~ GENERAL(ll);

replicate Weight;

run;
```

5.2.2A SAS command for MNL model with random effects

```
proc nlmixed data=Final METHOD=GAUSS GCONV=0.00000001 MINITER=3 G4=200;

parms         alpha2=-3.17        b_FixedDummy2=0.18        b_FRegularFlexShiftSchedule2=0.33
b_CPguaranteedRideHome2=0.32      b_Core2=0.27      b_Agglomeration2=0.20      b_Forenszone2=0.25
b_outsideAgglomeration2=0.30         b_Cporganisation2=0.15         b_ProbCarCONGESTION2=0.20
b_DTrainstationwithin1km2=0.09

alpha3=-3.92  b_FixedDummy3=-0.40  b_ProbCarCONGESTION3=0.22  b_ProbCarParkingCostEmployer3=0.13
b_DTrainstationwithin1km3=1.21     b_Core3=1.60     b_Agglomeration3=1.42     b_Forenszone3=0.14
b_outsideAgglomeration3=-0.01  b_AccessibilityMunicipality3=-0.29

alpha4=-4.61              b_FixedDummy4=-0.09              b_FRegularFlexShiftSchedule4=-0.10
b_FPTInfo4=0.05b_PTextrafee4=0.10      b_ProbPTtraveltime4=-0.07      b_DBusStopwithin500m4=1.26
b_Core4=1.42 b_Agglomeration4=1.46 b_Forenszone4=-0.37 b_outsideAgglomeration4=-0.44

alpha5=0.39            b_FixedDummy5=0.19            b_FBikeProvision5=0.06      b_BicyFee5=0.23
b_ProbBicyDangerousTraffic5=-0.09        b_ProbBicySocialInsecurity5=-0.04        b_Core5=0.68
b_Agglomeration5=-0.05 b_Forenszone5=0.14 b_outsideAgglomeration5=0.26  b_slopeMunicipality5=-
0.7 b_AccessibilityMunicipality5=-0.52 b_LogJobDensityMunicipality20055=-0.31

 t2=0.15 t3=0.003 t4=0.02 t5=0.07 t23=-0.11 t24=0.16 t25=0.09 t34=0.17 t35=0.07 t45=0.07;


Utility2=alpha2+b_FixedDummy2*FixedDummy+b_FRegularFlexShiftSchedule2*FRegularFlexShiftSchedul
e+b_CPguaranteedRideHome2*CPguaranteedRideHome+b_Cporganisation2*Cporganisation+
b_Core2*Core+b_Agglomeration2*Agglomeration+b_Forenszone2*Forenszone
+b_outsideAgglomeration2*outsideAgglomeration+b_ProbCarCONGESTION2*ProbCarCONGESTION+
b_DTrainstationwithin1km2*DTrainstationwithin1km+b_AccessibilityMunicipality3*AccessibilityMun
icipality + u2;


Utility3=  alpha3   +  b_FixedDummy3*FixedDummy   +  b_ProbCarCONGESTION3*ProbCarCONGESTION   +
b_ProbCarParkingCostEmployer3*ProbCarParkingCostEmployer+b_DTrainstationwithin1km3*DTrainstati
onwithin1km+b_Core3*Core+b_Agglomeration3*Agglomeration+b_Forenszone3*Forenszone
b_outsideAgglomeration3*outsideAgglomeration + u3;


Utility4=alpha4+b_FixedDummy4*FixedDummy+
b_FRegularFlexShiftSchedule4*FRegularFlexShiftSchedule+b_FPTInfo4*FPTInfo+
b_PTextrafee4*PTextrafee+b_ProbPTtraveltime4*ProbPTtraveltime+b_DBusStopwithin500m4*DBusStopwi
thin500m+b_Core4*Core+b_Agglomeration4*Agglomeration+b_Forenszone4*Forenszone
+b_outsideAgglomeration4*outsideAgglomeration + u4;


Utility5=alpha5+b_FixedDummy5*FixedDummy+b_FBikeProvision5*FBikeProvision+  b_BicyFee5*BicyFee
+b_ProbBicyDangerousTraffic5*ProbBicyDangerousTraffic+b_ProbBicySocialInsecurity5*ProbBicySoci
alInsecurity    +b_Core5*Core     +b_Agglomeration5*Agglomeration     +b_Forenszone5*Forenszone+
b_outsideAgglomeration5*outsideAgglomeration+b_slopeMunicipality5*slopeMunicipality+
b_AccessibilityMunicipality5*AccessibilityMunicipality+
b_LogJobDensityMunicipality20055*LogJobDensityMunicipality2005 + u5;
```

```
exp_utility2=exp(utility2);
exp_utility3=exp(utility3);
exp_utility4=exp(utility4);
exp_utility5=exp(utility5);
sum= 1 + exp_utility2 + exp_utility3 + exp_utility4 + exp_utility5;

if mode=1 then p_mode = 1/sum;
if mode=2 then p_mode = exp_utility2/sum;
if mode=3 then p_mode = exp_utility3/sum;
if mode=4 then p_mode = exp_utility4/sum;
if mode=5 then p_mode = exp_utility5/sum;

if p_mode>1e-8 then ll=log(p_mode);
 else ll=-1e10;

 su2=t2*t2;
 su3=t23*t23+t3*t3;
 su4=t24*t24+t34*t34+t4*t4;
 su5=t25*t25+t35*t35+t45*t45+t5*t5;
 cov32=t2*t23;
 cov42=t2*t24;
 cov43=t23*t24+t3*t34;
 cov52=t2*t25;
 cov53=t23*t25+t3*t35;
 cov54=t24*t25+t34*t35+t45*t4;

model mode~ GENERAL(ll);
random u2 u3 u4 u5 ~ Normal ([0,0,0,0],[su2, cov32, su3, cov42, cov43, su4, cov52, cov53,
cov54, su5]) SUBJECT=Arrondissement OUT=randomestimates;
replicate Weight;

ESTIMATE 'Var2' t2*t2;
ESTIMATE 'Var3' t23*t23+t3*t3;
ESTIMATE 'Var4' t24*t24+t34*t34+t4*t4;
```

```
ESTIMATE 'Var5' t25*t25+t35*t35+t45*t45+t5*t5;
ESTIMATE 'cov32' t2*t23;
ESTIMATE 'cov42' t2*t24;
ESTIMATE 'cov43' t23*t24+t3*t34;
ESTIMATE 'cov52' t2*t25;
ESTIMATE 'cov53' t23*t25+t3*t35;
ESTIMATE 'cov54' t24*t25+t34*t35+t45*t4;
title"Multinomial model with Random effects with PROC NL Mixed";
run;
```