The effects of teleworking on commuting patterns, modelled for the city of Almere

How to include teleworking in the traffic model of Almere?

Goudappel

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Preface

In front of you lies my master's thesis "The effects of teleworking on commuting patterns, modelled for the city of Almere", which serves as final piece of the master thesis Civil Engineering and Management with the track Integrated Urban Transport at the University of Twente, Enschede. This thesis research is conducted at Goudappel.

In line with the subject of this thesis, I have performed this thesis partly working from home, but luckily I had the opportunity to work at Goudappel. I want to thank my supervisors of Goudappel, Bastiaan Possel and Tanja Hardt and my supervisors of the University of Twente, Baran Ulak and Karst Geurs for their guidance and support throughout this thesis period.

I hope you enjoy reading my thesis.

Thijs Kroep
Enschede, November 2022

Summary

In 2020, the COVID-19 pandemic reached the Netherlands, and the Dutch government took measures to contain the infection rate. One of those measures was the (strict) advice to work from home. Although some people were already working from home before these measures were implemented, many people did not have (much) experience working from home. The COVID-19 pandemic thus showed opportunities to include teleworking in the working behaviour of people. An increase in teleworking could also have effects on commuting patterns and traffic intensities. The existing literature examined the development of teleworking during the pandemic and determined which characteristics caused people to work from home. However, not much was known about how teleworking would develop after the pandemic and which effects it could have on traffic intensities and commuting patterns when no advice to work from home is in place. The development of teleworking and its effects after the pandemic can be estimated using traffic models. In this study the 'Multimodal traffic model Almere' built in the Traffic modelling software OmniTRANS Expert is used to determine the effects of teleworking on traffic intensities and commuting patterns. The city of Almere is chosen because it is a city with a lot of transportation movements and is moreover closely located to cities such as Amsterdam and Utrecht, which makes Almere a ideal city to examine in- and outgoing commuting traffic. In this research, the following research question has been formulated:

What are the estimated effects of teleworking on traffic intensities and commuting patterns for residents of Almere and how can these effects be modelled?

This research is divided into three separate parts, in which analyses are performed that contribute to answering the research question. Firstly, teleworking and commuting behaviour before, during and after the pandemic was analysed to get an insight into the effects of the pandemic on teleworking. GPS data on transportation trips was retrieved from the NVP panel to perform this analysis. Commuting trips during twenty selected weeks before, during and after the pandemic were investigated. According to the results of this analysis, teleworking numbers increased strongly during the first weeks of the pandemic. In this period, between 50 and 55 per cent of the working days were performed from home. In the weeks after, the teleworking numbers weakened slightly to around 40 per cent. However, working from home remained on this level even after the pandemic faded and the measures were lifted. This indicates that people are willing to work from home even if there are no restrictions.

Secondly, it is analysed which people are working from home in the period after the pandemic. It is therefore determined which individual characteristics have an influence on teleworking and mode choice. Additional survey data on the same members of the NVP panel was used to gather information on individual characteristics of the persons making the trips. This step is divided into three separate parts for which each a regression analysis is performed. The first regression analysis is performed to determine the influence of individual characteristics on the probability that a person works from home in the analysed weeks after the pandemic. In the second regression analysis, the influence of individual characteristics on the change in the telework probability between the beginning of the pandemic and after all measures were lifted is examined. The third regression analysis determines the influence of individual characteristics on mode choice. For the first two analyses, a censored regression is performed, while the last is an multinomial regression analysis.

The regression analysis on the probability that a person teleworks in the selected weeks after the pandemic resulted in several relationships between the characteristics of the person and the teleworking probability. People working in the sectors healthcare and industry have an higher chance of working at their workplace, while office workers tend to work from home more often. Moreover,

people that indicated to perceive a higher productivity when working from home or indicated that they do not like commuting have a higher probability to work from home. People living in less densely populated areas were also more likely to be working from home than people living in more urban areas.

Furthermore, the influence of individual characteristics and the change in teleworking between the beginning and end of the pandemic showed several relationships. People with a higher age and people perceiving more pleasure working from home were more likely to increase or maintain working from home after the pandemic, while medium and higher educated people were more likely to decrease working from home after the pandemic.

The regression analysis to determine the impacts of individual characteristics on mode choice is performed four times for periods before the pandemic, during the first weeks of the pandemic, during the whole pandemic and after the pandemic. Teleworking has been added as mode of transportation to analyse changes between the other modes of transport and teleworking. From these four regression analysis it can be concluded that older, higher educated people living in less densely populated areas that work either in the ICT sector or have an office function have an increased likelihood to work from home. On the other hand, people with higher incomes, working in industry or healthcare, who own a car and/or driver's license and who live in a single household are more likely to prefer commuting by car over teleworking.

The multinomial regression analysis to determine mode choice for the period after the pandemic is used in the model of Almere to estimate the effects of teleworking on traffic intensities and commuting patterns. The model of Almere can be split into four steps, in which trips are generated, trips are distributed, the modal split is calculated and the trips are assigned to the network. In this research, only the step in which the modal split is calculated is adjusted. Furthermore, the model of Almere has 1400 zones and the regression model is used to recalculate the modal split between each combination of the zones. This resulted in traffic intensities and commuting patterns on the network of Almere that can be compared to the model of Almere without the implementation of teleworking.

By implementing teleworking in the model of Almere, decreases in car and public transport intensities were observed, while bicycle stayed around the same level. The highest decreases were observed during the morning rush hour. Public transport intensities decreased significantly with decreases between 40% and 60% on selected links. Bicycle intensities increased on long and continuous roads due to the recalculation of the modal split. On the other hand, decreases in bicycle intensities were observed on smaller roads, facing towards the city centre. The decreases of car intensities were the highest on access roads which connect Almere to its surrounding cities where it varied between 20% and 40% . The highest absolute decreases were visible on the bridge between Almere and Amsterdam.

Next to intensities, also differences in congestion and travel time were estimated for the car. The congestion was approached by looking at the Intensity-Capacity (IC) ratio on the roads. Due to the implementation of teleworking in the model of Almere, most high IC-ratios reduced, with as the result a lower chance of congestion. The reduction in travel time was determined for the routes between Almere and the surrounding cities; Amsterdam, Utrecht, Zwolle and Harderwijk. Although the traffic intensities decreased significantly, only small decreases were found in travel times between on these routes. Only for the route Almere-Amsterdam a travel time reduction of just over one minute in the morning rush hour was observed. In reality the reductions in travel time are expected to be higher, due to the fact that the model of Almere is a static model that determines travel times purely on intensity-capacity, while more factors affect the travel time.

The data used for the regression model that was used as input for the model of Almere was collected just after the advice to work from home was lifted. In this period, many people still worked from home, however, it is expected that a part of these people returns to commuting to the office. A sensitivity analysis is performed to determine the effects on commuting patterns and traffic intensities, if the number of people teleworking decreases. The results show that when the current teleworking numbers are reduced by 50%, teleworking still significant affects congestion and travel time. A reduction of 15% was determined to be the maximum reduction to prevent high IC-ratios and thus probably congestion between Almere and Amsterdam.

During the pandemic, teleworking seemed thus to be an alternative to commuting. Teleworking led to an estimated decrease in traffic intensities, especially for car and public transport. Moreover, a decrease in congestion and travel time for car traffic was observed due to the rise of teleworking. Even in future scenarios where teleworking is used to a lesser extent, it can still impact traffic intensities and commuting patterns. Working from home could thus be a solution to reduce traffic intensities, congestion, travel times.

Table of Contents

1. Introduction

In late 2019, the world came in contact with the COVID-19 virus for the first time. This highly infectious virus originated in China and spread quickly throughout the whole world, causing a lot of illness, hospitalizations and even deaths. The COVID-19 virus was soon categorized as a pandemic. Since this was a rather new situation and not much was known about this virus, there was no universal way of dealing with it and each country took their own measures to limit the infection rates. Some countries, such as China and Italy, introduced a strict lockdown, while other countries, such as Sweden, tried to let the virus circulate in a controlled manner.

At the start of 2020, the virus also reached the Netherlands. Instead of a strict lockdown or a minimum of measures, the Dutch government decided to introduce an 'intelligent' lockdown on March 23, 2020. The intelligent lockdown implies that although the advice is to stay at home, people are still allowed to go outside to go to work, do groceries or just take a walk. People who are infected with the virus should stay at home. Besides the 'intelligent lockdown', the government took general measures including washing hands on a regular basis, sneezing into the elbow, no more shaking hands and keeping 1.5-meter distance from each other. Another measure from the Dutch government to reduce infection rates was to close schools. As alternative online lessons were given (Rijksoverheid, 2021).

On March 12, 2020, even before the announcement of the 'intelligent' lockdown, the government issued the advice to work from home. Since then, the advice has been changed several times regarding the infection rates at that time. The advice over the last two years fluctuated between a relaxed advice to work from home, where people were allowed to work on location to stricter advice, where people are urgently requested to work from home and only work on location if necessary. Since the 15th of March 2022, the government abolished the advice (Rijksinstituut voor Volksgezondheid en Milieu, 2021). Moreover, during periods of the pandemic with more severe infection rates, the government also decided to close businesses, such as restaurants, event locations and contact professions (De Haas, Faber, & Hamersma, 2020).

Due to the measures of the government mentioned above, employees of companies and organisations located in the Netherlands are encouraged to work as much as possible from home. Especially in the first lockdown, many employees followed the advice of the government. Of course, it was not for everyone possible to work from home and every company and organisation dealt differently with the advice. For many businesses, working from home, also referred to as teleworking, was not the norm and the vast majority of the employees worked usually physically at their workplace. According to Belzunegui-Eraso and Erro-Garcés (2020), many companies and organisations in the EU were not prepared to deal with an emergency situation like the COVID-19 pandemic. And however an increasing number of European companies included teleworking in their collective plans and agreements, they did not apply to mass teleworking in the context of a pandemic (Belzunegui-Eraso & Erro-Garcés, 2020). However, the Netherlands was a forerunner when it came to teleworking in comparison to other European countries. In a large part of the EU member states, less than 15% of the people worked from home in 2019 pre-COVID times, while the Netherlands had a percentage of 37% of people who teleworked. It should be noted, however, that the majority of this proportion worked from home only sporadically (Milasi, González-Vázquez, & Fernández-Macías, 2021).

In the past, teleworking has been a point of discussion on several occasions. Already in the late last century, a policy document of the Dutch Ministry of Transport (Ministerie van Verkeer en Waterstaat, 1990) mentioned possible problems for the future of transport in the Netherlands. These problems include environmental problems and a decrease in accessibility and safety. According to an article from 1991 by Hamer et al. (1991), teleworking could help to tackle these challenges. They cite: "It was concluded that teleworking has resulted in a significant decrease in the total number of trips by teleworkers (−17%). Peak-hour traffic by car has been reduced even more (−26%)" (Hamer, Kroes, & Van Ooststroom, 1991, p. 365). Due to the ongoing COVID-19 pandemic, teleworking has become very relevant again, and therefore it is interesting to look at the effects of teleworking on mobility.

In this research, the effects of teleworking on commuting patterns are assessed for the city of Almere. Almere is a city in the Dutch province of Flevoland. It has approximately 212.000 inhabitants in 2020 and is located within 35 kilometres of the capital city of the Netherlands, Amsterdam. Due to its location, Almere can be seen as a commuter city with a relatively high number of external traffic movements. The high number of external traffic movements in combination with Almere's internal commuting movements make Almere an interesting city to analyse.

The master thesis "The effects of teleworking on commuting, modelled for the city of Almere" has the following structure. The first section is the research design, which consists of the research problem, research objective, research questions and the scope of the study. In the literature review, existing literature on teleworking (during the pandemic) and its effects on mobility are examined to determine what is already known about the topic of the research. The literature review also contains a theoretical framework and the rationale of the research. The literature section is followed by the methodological section. In this section, the methods that were used in the master thesis are described. The following two chapters present respectively the results of the data and the model analysis. Before the thesis ends by making conclusions, the methods and results of this study are discussed in the discussion section.

2. Research design

In the research design section, the research strategy of the master thesis is elaborated on. Firstly, the research problem is described. With the research problem in mind, the research objective and questions are formulated. This section ends with a view on the scope of the master thesis.

2.1. Research problem

In the previous section, an introduction to teleworking was given and it is more relevant than ever, due to COVID-19. Teleworking has increased enormously and its effects on traffic intensities and mobility patterns are visible. These developments in teleworking show that there are possibilities to trigger a mobility transition, with lasting positive effects for people and the environment. However, it is unsure how working from home will develop after the COVID-19 pandemic. To find out whether teleworking is also a feasible mobility solution after the working from home restrictions are lifted, it should be known how telework develops in this period and which people are going to work from home. An insight in who is going to work from home and the development of teleworking, offers the opportunity to include working from home in future mobility forecasts. This requires also the knowledge how teleworking can be implemented in existing mobility models. The mobility models of Goudappel are designed to forecast mobility situations and determine their causes and effects. Including teleworking in these models would make these models even more realistic and useful. Ultimately, more accurate information on the development of teleworking and its effects on mobility will help to give better-informed advice on mobility policies.

2.2. Research objective

In the previous section, the research problem has been clarified. Teleworking is getting more relevant in the mobility sector and it expected to have lasting impacts on mobility. Therefore, it should be known which people are going to work from home, how teleworking develops after the COVID-19 pandemic and how it can be included in existing mobility models to forecast its impacts on mobility, so this could be taken into account in new policies or plans. In the thesis, model Almere is used to forecast the effects of teleworking on commuting patterns. The following research objective is defined:

To determine who is going to work from home and how teleworking will develop after the COVID-19 pandemic and research how these findings can be implemented in the existing mobility model of Almere to find out its possible effects on traffic intensities and commuting patterns for the city of Almere.

2.3. Research questions

Based on the research objective written down in the previous section, research questions can be drawn up. The main research question can be directly taken from the objective and reads as follows:

- *What are the estimated effects of teleworking on traffic intensities and commuting patterns for residents of Almere and how can these effects be modelled?*

To answer the main question, several sub-questions have been formulated. The sub-questions are listed down below:

- *Which mobility patterns of commuting trips can be extracted using available data collected during the COVID-19 pandemic?*
- *Which individual characteristics affect the probability of teleworking and what changes in teleworking and mode choice can be observed?*
- *How can the impact of individual characteristics on mode choice be implemented in the model of Almere and what changes in traffic intensities and commuting patterns can be observed?*

2.4. Scope

In this section, the scope of the research is described briefly. This thesis focuses on the effects of teleworking on traffic intensities and commuting patterns, for the city of Almere. To do this regression analyses and an analysis in OmniTRANS are performed during this research.

Data on trips made by the respondents of the NVP panel is used to determine the relationship between individual characteristics and teleworking and mode choice. The relationships between individual characteristics and mode choice are used as input data for the model of Almere. Here, it is important to mention that for the mode choice, the conventional modes car, public transport and bicycle are taken into account. However, teleworking, or staying at home, is added as a new mode of transport. The effects of teleworking on commuting patterns resulting in the model of Almere are assessed on traffic intensity, modal split, congestion and travel times between Almere and Amsterdam.

In this research, the 'Multimodal traffic model Almere' built in the Traffic modelling software OmniTRANS Expert is used in which the effects of teleworking need to be incorporated. This research, therefore, focuses on implementing teleworking in an existing model, rather than building a model. The modal split will be recalculated using the relationship between individual characteristics and mode choice to implement teleworking into the model of Almere. The model Almere in this research is chosen for several reasons. First of all, Almere is a relatively big city with a lot of travel movements, both internal and external. Furthermore, model Almere is a complete multimodal model and therefore has a lot of possibilities. The model is also relatively small, which means that it has relatively low computation times. Perhaps the most interesting reason, many inhabitants of Almere have a job outside of Almere, mainly in Amsterdam. Almere has thus many internal and external commuting traffic.

3. Theoretical framework

In the previous chapter, the research problem, objective and questions have been discussed. That chapter indicated the direction of this research. Before diving into the research needed to answer the research questions, the existing information on this topic should be reviewed. The theoretical framework, therefore, provides an overview of the existing theories found in the literature. Figure 1 presents the conceptual model containing concepts and relations relevant to the topic of the research. During the theoretical framework, these concepts and the relations between these concepts are discussed. This is done in three paragraphs, each of which encompasses several concepts from Figure 1. The first paragraph focuses on the impact of the COVID-19 pandemic on teleworking and includes all concepts in block of research question 1. The COVID-19 pandemic is not the only factor influencing teleworking. Other factors that impact teleworking are discussed in the second paragraph and the concepts of this paragraph are visualised in the block of research question 2. The block of research question 3 contains the concepts discussed in the third paragraph which is about the effects of teleworking on mobility. Since it is the main subject of the research, the concept of teleworking is discussed in each of the paragraphs. After the discussion of the literature, this chapter provides a rationale for the research.

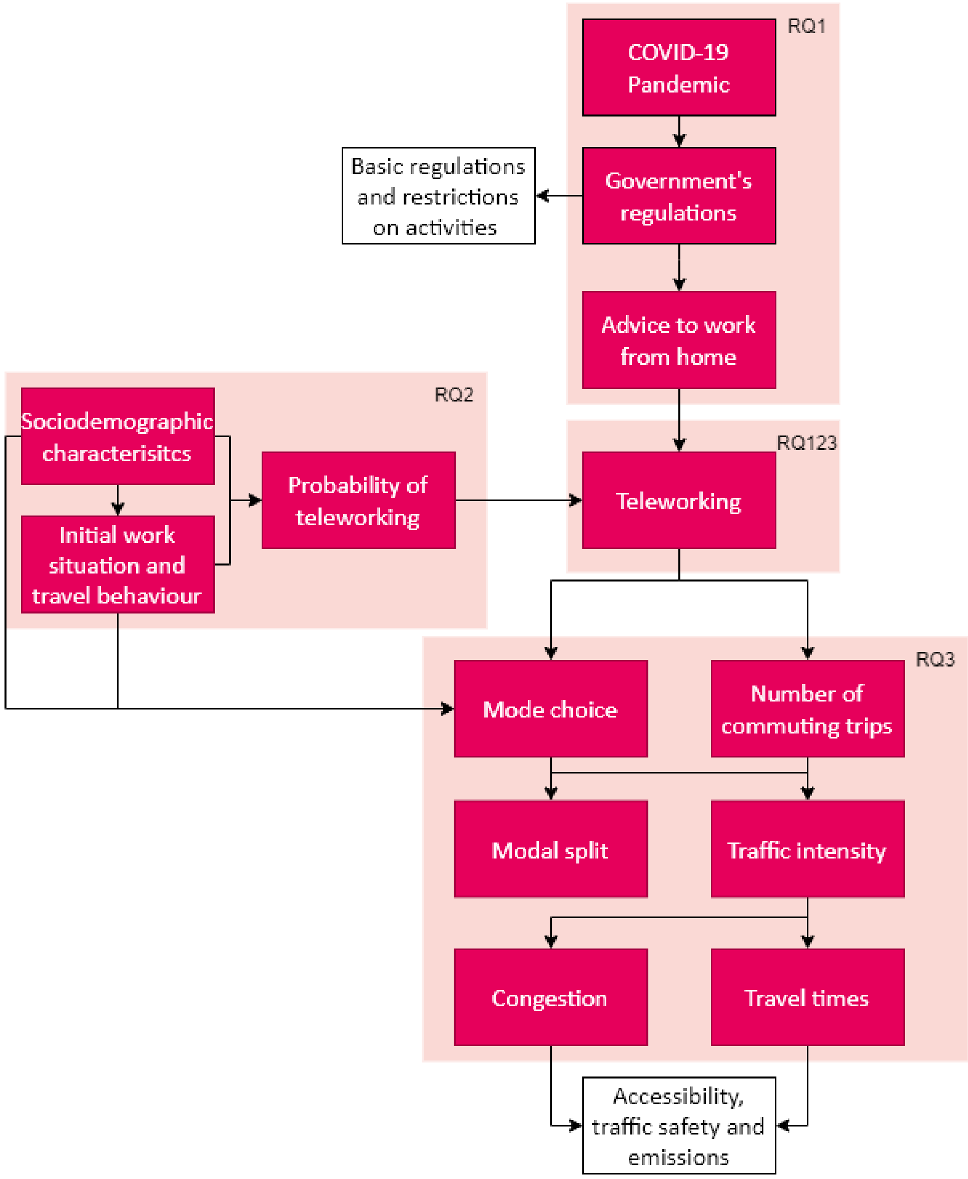

Figure 1 - Conceptual model of the study, concepts indicated with pink are within the scope of the study

3.1. COVID-19 pandemic affecting teleworking behaviour

As has been stated in the introduction, the COVID-19 pandemic has induced many Dutch workers to change their work situation. According to a survey study performed by De Haas, Faber and Hamersma (2020), the work situation of about fifty per cent of the workers changed due to the measures the government took to contain the virus. The change in the work situation often included working from home. Roughly 44% of the respondents to the survey started teleworking or is going to work from home more often (De Haas, Faber, & Hamersma, 2020). In total, the number of people working at least 75% of their hours from home increased from 6% in 2019 to 39% during the first intelligent lockdown. Online meetings became more popular during the pandemic, with a reported increase of 30% of the workers (De Haas, Faber, & Hamersma, 2020).

3.2. Other factors (individual characteristics) impacting teleworking

In the previous section, the effects of teleworking observed during the lockdown were discussed. Whether people are going to telework is not only dependent on the regulations of the government. There are a lot of individual characteristics which contribute to the choice to work from home. These individual characteristics include demographic characteristics and geographical characteristics. In this section, literature on the effects of these individual characteristics is reviewed to find patterns.

3.2.1. Demographic characteristics

Individual characteristics can play an important role in the travel behaviour of people regarding commuting. People who have a higher risk of illness and hospitalization when infected with COVID-19 are probably more likely to work from home. Especially for people of older age, the pandemic can be an incentive to avoid social contact and stay at home. This has also been concluded by De Haas et al. (2020), who stated that older people are less active during the pandemic due to the fear of becoming infected. On the other hand, already before the pandemic older people (age 65 and above) were much less active than younger age groups. The cause for this is that people in this age group are often retired and thus do not work or go to school. Therefore, compared to younger age groups a much lower decline in travel time is observed by Van der Drift et al. (2021). Although some relations between age and teleworking are found in the literature, the findings on the impact of age on the probability of teleworking are mixed and largely influenced by the pandemic. A clear relationship between age and teleworking is thus not identified.

The influence of received education and income class on travel behaviour during the pandemic can more clearly be seen. Students and people who received higher education used relatively more often public transport for commuting before the pandemic. During the lockdown, these are the groups that are more likely to work or study from home (Hjorthol, 2006; Astroza, et al., 2020; De Haas, Faber, & Hamersma, 2020). Also, the income class of people contributed to the change in the work situation. Before the pandemic, people with high incomes had the largest travel time, however, this group of people caused the largest decrease in travel time during the pandemic. This shows that people with a higher income level are more likely to be able to work from home and reduce travelling (Van der Drift, Wismans, & Olde Kalter, 2021). Therefore, it can be assumed that people in higher functions can more easily work from home than people in lower functions.

Although the government's advice was to work from home during the 'intelligent lockdown', this is not for everyone possible. While office workers can often easily work from home, people with physical jobs often have to be present at the work location to perform their jobs (De Haas, Faber, & Hamersma, 2020; Belzunegui-Eraso & Erro-Garcés, 2020). The probability of teleworking is also affected by the employee's telework facilities and internet connection at home (Alizadeh, 2012; Olde Kalter, Geurs, & Wismans, 2021), and the adaptation of the employer to the advice (Belzunegui-Eraso & Erro-Garcés, 2020). For some jobs, small adaptations can be made to enable employees to work from home

(Belzunegui-Eraso & Erro-Garcés, 2020). This is for example the case in the sector of automation and IT. However, there are also jobs or functions in which it is much harder for people to telework. In sectors such as healthcare and retail, people often need to be physically present at the working place, making teleworking more difficult (De Haas, Faber, & Hamersma, 2020). Moreover, the attitude of employers towards teleworking impacts teleworking numbers. While some employers adopt the teleworking advice, others still prefer their employees to be present, even when they are ill (Belzunegui-Eraso & Erro-Garcés, 2020). The advice of the government caused thus not everyone to work from home, due to jobs or employers that do not allow employees to work from home.

3.2.2. Geographical characteristics

At the very beginning of the pandemic, especially the south of the Netherlands was struck by COVID-19 infections. However, quickly after, in other regions of the Netherlands, people got also infected with COVID-19. The regulations by the Dutch government were therefore implemented on a national scale, meaning that they applied to all regions of the Netherlands. According to De Haas et al. (2020), there was not a clear difference in outdoor activities between regions during the lockdown. They concluded that these findings indicated that people rather adjust their travel behaviour to the regulations set by the government than to the number of infections in their region. This argumentation is also supported by the fact that, according to 90% of the respondents, the regulations by the government are the main reason to stay at home (De Haas, Faber, & Hamersma, 2020).

It seems that the location of residence within the Netherlands does not contribute to how people react to the COVID-19 pandemic in terms of travel behaviour. This is mainly due to the nationwide regulations of the government. The lockdown did, however, show a difference in cycling behaviour in urbanised areas. Before the pandemic, the average cycling travel time was significantly higher in these areas than in non-urbanised areas. During the lockdown, the travel times of cycling in urbanised areas were reduced to the travel times of cycling in non-urbanised level. This could be explained by the decrease in public transport use, for which the bicycle was used as a first- and/or last-mile solution (Van der Drift, Wismans, & Olde Kalter, 2021).

The location of residence has a direct influence on commuting distance. When people are living further from their workplace, their commuting distance is greater. A long commuting distance may increase the likeability to work from home. On the other hand, teleworking makes it more attractive to live further from the work location, especially when the house prices outside urban areas are much lower (Helminen & Ristimäki, 2007; De Abreu e Silva & Melo, 2018).

3.3. Effects of teleworking on traffic intensities and commuting patterns

Due to the COVID-19 pandemic and the subsequent advice to work from home, teleworking numbers have multiplied. This has an impact on a wide range of things, but in this research, the effects on mobility are going to be investigated. These effects can be divided into short- and long-term effects. Short-term effects being the effects that are observed during the first stage of the pandemic and long-term effect are the estimated effects of teleworking in the future. Due to the relatively recent nature of the pandemic, short-term effects are more likely to be found than long-term effects. However, literature on both short- and long-term effects of teleworking on mobility is analysed in this section.

3.3.1. Short-term effects

Since the Dutch government communicated the first measures, various short-term effects on mobility can be seen. Anticipated effects of increased teleworking include a decrease in the number of trips, travel distance and travel time. These effects were also observed during the first 'intelligent' lockdown, with a reduction of respectively 55% and 68% in both the number of trips and travel distance in comparison to 2019 (De Haas, Faber, & Hamersma, 2020). Also, commuting trips showed a decrease during the government's restrictions. A direct effect of teleworking is a decrease in the number of commuting trips; people working from home go less often to their workplace and therefore contribute to fewer commuting trips (De Haas, Faber, & Hamersma, 2020). A lower number of trips also indicates a decrease in the average travel distance per week. Although teleworking has a decreasing effect on the number of trips, they tend to become longer. According to Ravalet & Rérat, (2019), a decrease in commuting trips due to teleworking will be compensated by either more trips for other purposes or by longer commuting trips. Ultimately, a reduced traffic intensity can be linked to a decrease in congestion and emissions while increasing accessibility and traffic safety (Hamer, Kroes, & Van Ooststroom, 1991). Moreover, the air quality will be promoted due to a reduction in emissions (Giovanis, 2018).

The pandemic shows that teleworking might be a feasible alternative for commuting and can even trigger a change in mobility. Moreover, teleworking might be a powerful solution to reduce traffic volumes and improve air quality (Giovanis, 2018). In the Netherlands teleworking can therefore contribute to meeting climate targets. However, teleworking in other countries might be not as successful as in the Netherlands, since Dutch employees often have access to internet with high quality (Olde Kalter, Geurs, & Wismans, 2021).

The regulations of the Dutch government do not only have impacts on the number of trips, the travel distance and travel time, but also on the transportation mode used for commuting trips. According to Van der Drift et al. (2021), trips by car and bicycle were reduced by almost 50% during the COVID-19 pandemic. However, the distance travelled by bike and the travel times of cycling remained constant. Moreover, a decrease in bicycle trips can be explained because cycling trips often served as a solution for the first or last mile to and from public transport stops.

Furthermore, schools were closed, and students often use the bike as a transportation mode. Cycling could thus be an alternative option for the car in commuting trips, which will cause a positive impact on sustainability and accessibility (Van der Drift, Wismans, & Olde Kalter, 2021). According to Elldér (2020), a person who teleworks is less likely to drive a car, while the use of active modes is higher among teleworkers.

However, the COVID-19 pandemic also showed a negative impact on mobility in terms of mode choice. Public transport, often seen as a sustainable way of travelling, saw a steep decline of 90% in usage during this period (De Haas, Faber, & Hamersma, 2020). Three main reasons can be identified for this decrease. Firstly, the Dutch government urged to not use public transport when not necessary. Moreover, people might not want to travel by public transport, since they can get infected using public transport (De Haas, Faber, & Hamersma, 2020). The last reason that public transport use declined is that students and people with higher education, who are more likely to use public transport, started to work or study more often from home (De Haas, Faber, & Hamersma, 2020; Van der Drift, Wismans, & Olde Kalter, 2021). However by lifting basic COVID-19 regulations in the future, public transport might be an alternative for teleworkers who used to commute by car (Van der Drift, Wismans, & Olde Kalter, 2021).

The pandemic could have significant lasting effects on mobility if car trips will be substituted regularly by trips by bike and if the decrease in public transport usage is not structural and people start travelling by bus and train again after the pandemic (Van der Drift, Wismans, & Olde Kalter, 2021).

3.3.2. Long-term effects

Due to the decrease in mobility and the resulting beneficial side effects, the COVID-19 pandemic showed an opportunity for countries to promote teleworking in order to accelerate the mobility transition (Van der Drift, Wismans, & Olde Kalter, 2021). The Dutch government could thus make efforts to promote teleworking to achieve a reduction in traffic and even an acceleration in the mobility transition, however, many employees do not have the option to work from home (Olde Kalter, Geurs, & Wismans, 2021). The government should accept the challenge to ensure that people continue to work from home, also after the pandemic. Teleworking might thus sound like a great opportunity to reduce emissions and congestion while improving air quality and meeting climate targets.

Kennisinstituut voor Mobiliteitsbeleid (KiM) performed research concerning the long-term effects of the COVID pandemic on commuting trips (Hamersma, Krabbenborg, & Faber, 2021). In their report, they determined expected mobility effects. Most interesting is their expectation that people will more often work from home. This expectation is supported by the findings of De Haas et al. (2020), who conclude that 27% of people that started or increased teleworking during the pandemic expect to be working from home more frequently in the future than before the pandemic. Furthermore, meetings will likely be held online more often in the future. Also, an increase in online home education is expected, however, this expected increase is much smaller and home education is likely to be often additional to physical lessons (De Haas, Faber, & Hamersma, 2020; Hamersma, Krabbenborg, & Faber, 2021).

These expected trends will cause a change in commuting trips, including a change in transportation mode and the spread of trips over the week or day (Hamersma, Krabbenborg, & Faber, 2021). More importantly, a significant contribution to the mobility transition can be made, when the expected trends become reality. This is largely dependent on how employers will deal with teleworking in the future (De Haas, Faber, & Hamersma, 2020). Whether the expected effects will come true after the pandemic depends also on the behaviour of people and the policies to be pursued.

3.4. Rationale for the research

The existing literature mostly explores the effects of teleworking on commuting behaviour during the COVID-19 pandemic and how this has changed compared to before the pandemic. There is, however, not much known about how teleworking will develop after the COVID-19 pandemic and what will be the impact on commuting patterns and traffic intensities. This master thesis research will expand on the existing literature by implementing teleworking in a traffic model which can be used to estimate the effect of teleworking on traffic intensities and commuting patterns. Moreover, the effects of characteristics on telework behaviour are researched. These insights will be used to determine which characteristics are of importance and should be included in the determination of teleworking probabilities. The focus of the study on the city of Almere allows for examining the effects of teleworking on commuting patterns case study-wise. The outcomes of this research will contribute to the understanding of factors affecting teleworking and the impact of teleworking on commuting patterns. The master thesis research 'The effects of teleworking on commuting patterns, modelled for the city of Almere' will therefore be an addition to the already existing literature on teleworking and its effects on commuting behaviour.

4. Methodology

As explained in the research design, this research is focused on determining the effects of teleworking on commuting patterns in Almere and how these are modelled. This methodology section provides methods to answer the research questions set in paragraph 2.3. To get a clear overview of the methods used to answer each research question, the structure of the research is presented in Figure 2. In the structure of the research, the methods are linked to the research questions.

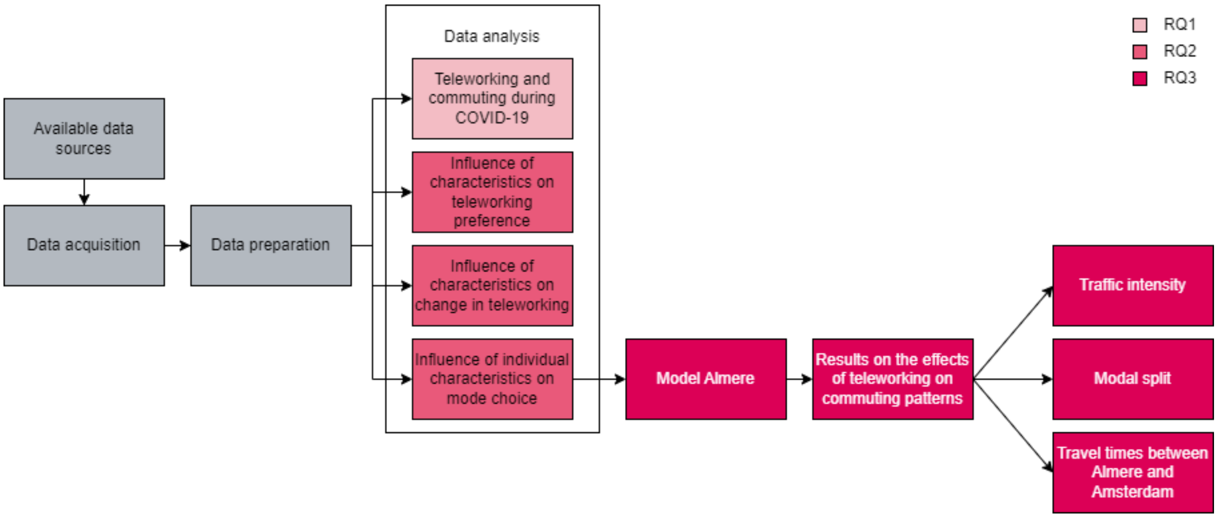

Figure 2 - Structure of the research

The research starts with the acquisition of data from available data sources. When the data is collected, the data is prepared for data analysis. The data analysis can be divided into four parts. The first part is about the development of teleworking and commuting during the COVID-19 pandemic and is performed to get an answer to the first research questions. Moreover, the influence of characteristics on teleworking, change in teleworking and mode choice are analysed. These three analyses were performed to get an answer to the second research question. The results of the influence of individual characteristics on mode choice are then implemented in the model of Almere. The third research question is focused on the implementation of teleworking in the model and the resulting outcomes. The model of Almere uses the found relationship between characteristics and teleworking to generate results on the effects of teleworking on commuting patterns. These results are then assessed based on the traffic intensity, modal split and travel times between Almere and Amsterdam. This methodology starts with sections about data acquisition and data preparation. After this is explained, there are four sections consisting of the methods that are used to answer one of the research questions each.

4.1. Data acquisition

In this research, multiple analyses were performed, which give a better understanding of teleworking and its effects on commuting patterns. Before these analyses were performed, data on teleworking is gathered. Moreover, data on travel behaviour and individual socio-economic characteristics were needed to determine which people are going to work from home. In this section, it is briefly explained which data is gathered from where during this research and for what purpose the data is used.

Mainly, the NVP data is used for the data analysis part of the master thesis. The NVP data is a recently introduced data source that contains GPS data on travel behaviour, travel motives and mode choice of about 10,000 respondents. Besides the GPS data of the trips that the respondents make, the NVP data also contains information on the individual characteristics of the respondents. These characteristics include age, gender, income level, received education level, employment status and the ownership of car and driver's licence, but also information on living location, work location and the households of the respondents. The data from the NVP is analysed during this research to find information on teleworking effects on mobility, but also on individual characteristics of people to find which characteristics influence the probability of working from home. The NVP data is very recent and includes data from during the pandemic. Unfortunately, the NVP does not contain any data on respondents who telework. The teleworking numbers are therefore determined based on the change in commuting trips occurring during the pandemic relative to before the pandemic. To analyse this difference in commuting trips, data is selected from the summer of 2019, shortly before the pandemic, until now. Only trips with an origin or destination within the municipality of Almere are selected to reduce the number of trips, which is beneficial to make the data analysis more manageable. This selection resulted in over 308,960 trips of 7491 respondents.

Table 1 - Available data sources for the master thesis

Data source	Description of the data
NVP (Nationaal Verplaatsingspanel)	NVP is a large-scale national data source containing data about travel behaviour, travel motives, mode choice and background characteristics of the Dutch population. This data is collected by recording the travel behaviour of approximately 10,000 participants. This data source is active since 2019 and contains useful data on the change in travel behaviour during COVID-19.
Survey data (Ministry of Infrastructure and Water Management, 2020)	The survey was conducted in 2020, during the start of the pandemic, among the NVP panel members and therefore adds extra information to the data of the NVP. About 3,000 of the 10,000 NVP panel members participated in the survey.
Mobiliteitsspectrum	Mobiliteitsspectrum is a database that contains intensities and origin and destination patterns of cars, public transport and cyclists. This database uses different data sources among which the NVP and is largely available in OmniTRANS.
CBS in uw buurt	CBS in uw Buurt (translated: CBS in your neighbourhood) is an open data source on neighbourhoods in the Netherlands. This data source contains information on about 75 different characteristics of the neighbourhoods and their inhabitants. This information ranges from demographics to information on traffic and transport.

In addition to the tracking data, a survey was conducted among the same members of the NVP (Ministry of Infrastructure and Water Management, 2020). This survey was conducted at the beginning of the pandemic and resulted in additional data from over three thousand respondents. The data contained extra information about individual characteristics, such as the working field and job function. Furthermore, the respondents of the survey were asked several questions about their situation during the pandemic and how they experience teleworking.

Although the NVP and its additional survey data are used as the main source for the data analysis of the research, other sources were needed in this research. An overview of the data sources used in this research including a description of which data they contain can be found in

.

4.2. Data preparation

In the previous section, raw data is gathered, which can be used to perform analyses on. Before the gathered data can be analysed, it is important that the data is interpretable and contains the needed information and, therefore, data preparation is needed. In this section, all data preparation steps that were taken to get the desired data sets are described.

4.2.1. Selections of weeks

The NVP started in 2019 and thus has data on trips from 2019 until the writing of this thesis. In this period, the NVP collected information on millions of trips. To ease the analysis of these trips, a selection of trips has been made from different periods between the beginning of 2020, shortly before the pandemic, until May of this year, 2022 has been selected. During this period, the COVID pandemic

Data source	Description of the data
NVP (Nationaal Verplaatsingspanel)	NVP is a large-scale national data source containing data about travel behaviour, travel motives, mode choice and background characteristics of the Dutch population. This data is collected by recording the travel behaviour of approximately 10,000 participants. This data source is active since 2019 and contains useful data on the change in travel behaviour during COVID-19.
Survey data	The survey was conducted in 2020, during the start of the pandemic, among the NVP panel members and therefore adds extra information to the data of the NVP. About 3,000 of the 10,000 NVP panel members participated in the survey.
Mobiliteitsspectrum	Mobiliteitsspectrum is a database that contains intensities and origin and destination patterns of cars, public transport and cyclists. This database uses different data sources among which the NVP and is largely available in OmniTRANS.
CBS in uw buurt	CBS in uw Buurt (translated: CBS in your neighbourhood) is an open data source on neighbourhoods in the Netherlands. This data source contains information on about 75 different characteristics of the neighbourhoods and their inhabitants. This information ranges from demographics to information on traffic and transport.

reached the Netherlands, the government took measures to reduce the infection rates including varying advice to work from home. In the last few weeks of the selected period, the government decided to lift all the measures. Between the initiation and the abolishment of the measures, different regulations were implemented. To find differences in teleworking during the COVID period, the selection consists of data from different weeks before, during and after the pandemic.

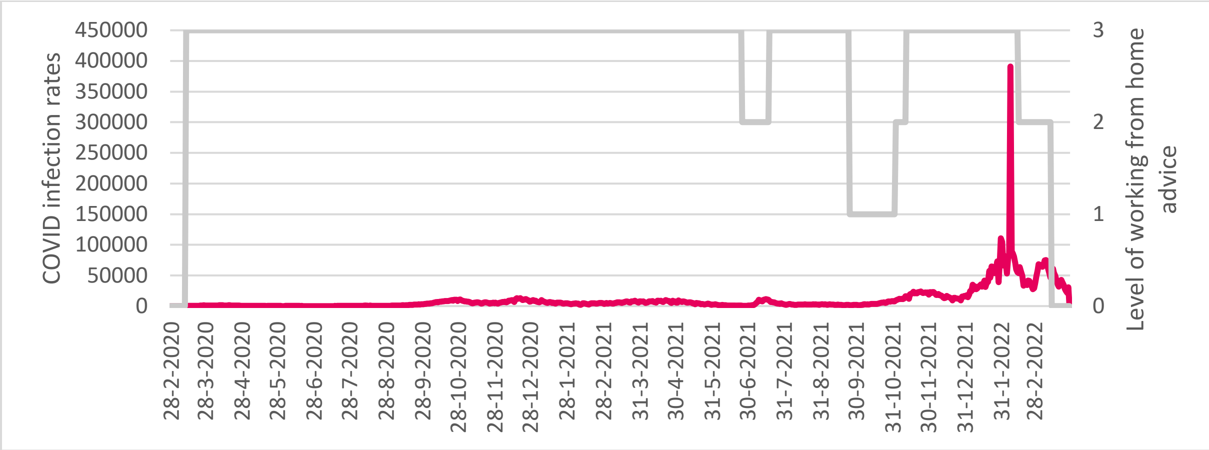

Figure 3 - COVID-19 infection rates and level of working from home during the pandemic (Rijksinstituut voor Volksgezondheid en Milieu, 2021)

Four different levels of the working from home advice are identified (Rijksinstituut voor Volksgezondheid en Milieu, 2021). These include a strict advice to work from home (level 3), an advice to work from home at least half of the time (level 2) and a more loose advice to work from home when it is possible (level 1). When there is no telework advice in place, level 0 is applicable. The working from home advice during the pandemic is presented in Figure 3 together with the infection rates at that time.

Table 2 - Selection of weeks used in this research

Year	Week	Start date	End date
2020	6	03-02-2020	23-02-2020
	7		
	13	23-03-2020	05-04-2020
	14		
	37	07-09-2020	13-09-2020
2021	27	05-07-2021	18-07-2021
	28		
	41	11-10-2021	07-11-2021
	42		
	43		
	44		
2022	7	14-02-2022	27-02-2022
	8		
	13	28-03-2022	15-05-2022
	14		
	15		
	16		
	17		
	18		
	19		

As can be seen in the figure, in a large part of the pandemic the most strict advice to work from home was applied. However, in 2021, the government reduced the strictness of the telework advice three times, fluctuating between level 1 and level 2 advice. As of the 15th of March 2022, the advice to work from home was completely lifted and has not been applied until the writing of this thesis.

To determine the effect of the teleworking advice on the working from home numbers, data has been selected from different weeks in the period from begin 2020 until now. As a reference, data from weeks shortly before the pandemic had been selected. These weeks include the most recent pre-COVID data and are therefore particularly suited to be compared with. The reference data are compared with data from during and after the pandemic. The weeks during the pandemic were selected based on the working from home advice that was applied at that time. For each level of working from home advice, several weeks are selected. Data after the lifting of the working from home advice was also selected to see whether patterns that originated during COVID-19 remained after the measures were lifted. An overview of the selected weeks can be found in Table 2.

4.2.2. Determine commuting and teleworking days

After gathering the NVP data for the selected weeks, the data still needs some adjusting before it can be used in the regression analyses. Each individual in the NVP and survey data has a unique TrackerID, which is paired with the trips made by that person as well as with individual information.

The gathered NVP data contains over three million trips to which a mode of transportation, a purpose, a day and time and a person and their attributes are attached. When filtering all the trips with the purpose work/business, 484,300 trips are left. In the NVP, the mode of transportation is determined for each of the trips based on the route and speed of the trip. With this information, it can be established which transportation mode is used for commuting. In some cases, however, more than two commuting trips (sometimes even with multiple modes) were made on the same day. After an analysis of these trips, three main causes could be identified. Multiple trips and trips with differing modes of transportation could both be a result of faults in the NVP data. In the limitations part of this thesis, this is elaborated on. Another cause is that a commuting trip is sometimes split up into two or more trips. A person can have added another destination to the commuting trip, such as a visit to the supermarket. It can also be that trips are split up because people are travelling with multiple modes of transport to their work. For example, to reach public transport a person might have to walk or bike. Lastly, the purpose of work/business contains commuting trips, but also business trips. A person can make multiple business trips in one day while using another mode of transportation for commuting. Ideally, these purposes would be separated into two purposes, however, this was not an option. It is therefore assumed that all work/business trips are commuting trips.

To prevent double counting of trips due to any of the just named reasons, commuting trips are aggregated to working days. It is assumed that when a person makes at least one work-related trip on a day, this person works on that day. When multiple modes are used for work/business trips on a single day, the mode with which the most distance is travelled on that day is selected as commuting mode. In the case that two modes of transport are used for an equal distance, the mode of transport most used by the respondent over all commuting trips is then selected. In some rare cases, two modes of transport are tied on both the distance travelled and the favourite mode for commuting. When this is the case, one of the two modes was assigned manually.

Now it is established when the persons are making commuting trips using which mode of transport, it can also be determined when they are working from home. In order to do so, a reference week is set, which is the first week of the selected weeks (week 6 of 2020). The reference week is a week close before the pandemic and has therefore the most recent data in the normal situation. The trips in the weeks during the pandemic are then compared with this reference week to see whether people decreased their number of commuting trips due to measures applied by the government. Not all NVP panel members contributed to the panel throughout the entire time, so before it could be determined if people were working from home, it should be specified whether they were actively contributing to the NVP panel in the research during that week. A person was labelled as active when they were making at least one trip in the selected week, regardless of the purpose of the trip. For every selected week, all active people are selected, and it is determined if they work from home by comparing the number of working days in that week to the number of working days in the reference week. When a person has a decrease in working days, it is assumed that this decrease is compensated by working from home days. If, for example, a person works four days in the reference week, but just two in the selected week, this person would thus be working from home the other two days.

The period after the pandemic contained several national holidays, among which Good Friday, Easter King's Day and Liberation Day. In case of a holiday, most people have a day off and to prevent that is wrongly assumed that these persons are working from home, trips made on these days were removed from the dataset and not included in the data analysis.

Similarly to other weeks, teleworking numbers are calculated for the two selected weeks before the pandemic. To determine the number of people that is working from home before the pandemic, a reversed method has been applied. The mean number of working days per person over all the other weeks is compared to the working days in the two weeks pre-COVID to see whether a person increased the days they are commuting. If this is the case, it is assumed that this person is working from home in the weeks before the pandemic.

4.2.3. Selecting independent variables

In the previous steps of the data preparation, commuting and teleworking days per person are identified. This information can be useful to make predictions about whether a person makes a commuting trip or stays at home to work. To make these predictions, regression models are created. Regression models determine the correlation between independent variables and a dependent variable. In this paragraph, the initial selection of independent variables is explained.

The NVP contained already a lot of information on the person making the trip. Moreover, the Ministry of infrastructure and Water Management (2020) conducted an additional survey among the NVP panel members to gather even more information on them, such as job type and experiences with working from home. From both the NVP data and the survey data, independent variables were extracted. Table 3 gives an overview of all of the included independent variables and their source.

Independent variables can be different types of data. Age, travel time, accessibility and household size are discrete types of data while education, income, urban density, pleasure and productivity are all ordinal data. The other independent variables are all nominal data.

All variables that have ordinal or nominal types of data are either binary or categorical. The gender of a person is in the NVP data either defined as man or woman, while car and driver's license ownership can be either true or false. These variables are therefore binary.

The categorical variables include all more than two categories. Both pleasure and productivity consist of five ordered classes. These classes indicate whether a person experiences a change in productivity or pleasure while working from home. For both of the variables, these classes are on a scale from much less to much more.

The variable income includes the income classes minimum, lower than modal, modal, one to two times modal, two times modal and higher than two times modal. To reduce the number of classes and thus increase the difference among them, some of these classes have been merged into a more comprehensive class. The class minimum was added to lower than modal, modal and one to two times modal are aggregated to modal to two times modal, while two times modal and higher than two times modal are merged into the class two times modal or higher.

Table 3 - Independent variables included in the regression analyses

Independent variable		Data source
Age		NVP
Gender		
Education level		
Gross annual income		
Urban density of living location		
Household size		
Household composition		
Driver's license		
Car ownership		
Sector	Industry	Survey
	Construction	
	ICT	
	Healthcare	
Function	Office	
	Management	
	Research	
	Education	
Reason teleworking	Government	
	Employer	
	Not pleasant	
	Already teleworking	
Pleasure		
Productivity		
Travel time by car		Goudappel
Accessibility of job location		Calculated

Also, for education level and urban density, classes were aggregated. Education level lower education includes former classes primary school only and lower secondary education, while medium and higher secondary and medium tertiary education have been classified as medium education. People that have finished bachelor, master or doctoral education fall within the class of higher education. For urban density, five classes were identified by the NVP. The two classes with the lowest density are combined into a new class low density, while the two highest classes are merged and redefined as high density. The middle class was not merged and is now called medium density.

The travel time is determined based on the living and job location of each of the NVP panel members. The NVP contained per person a four-digit postal code (PC4) in which their house is located, while the additional survey included a PC4 code of the job location. To determine the travel time for commuting, the travel time between the home and work postal code zones is used. These travel times were extracted from a matrix provided by Goudappel.

In combination with the population size per PC4 area, this travel time matrix is then also used to determine the accessibility of the job location. Firstly, the population of each of the origin PC4 areas is established using data from the CBS (2019). It is assumed that from each origin zones, persons could go to work in each destination zones. However, it is becoming less likely that a person commutes to their workplace when the travel time increases. Therefore, for each origin to each destination, the number of people from the origin zone is divided by the travel time. In this way, the number of people that can reach a zone is weighed based on the travel time. Work locations located in a PC4 zone that is within a reasonable travel time of PC4 zones with high numbers of inhabitants will have higher accessibility than work locations that are located in less densely populated areas.

Multiple independent variables included data, which was UNKNOWN, these are assumed to be empty. In a later stadium of this research, the number of variables is downscaled based on whether they improve or decrease the goodness of fit of the regression model.

4.3. Analysing the effects of COVID-19 on teleworking and commuting patterns

The COVID-19 pandemic showed a great opportunity in implementing teleworking in the commuting behaviour of people. During this master thesis, teleworking behaviour is analysed and implemented in the model of Almere to determine the changes in teleworking and their effects on commuting patterns for the inhabitants of Almere. During the different stages of the ongoing pandemic, the government implemented several degrees of the working from home advice. These included a strict advice to work from home, an advice to work from home at least half of the time and a more flexible advice that allowed employees to work from their workplace. The different situations as a result of the fluctuating advice to work from home can be used to analyse a change in travel behaviour during different lockdown intensities. Therefore, commuting patterns are analysed during different intensities of the telework advice.

NVP data was used to get an overview of which mode of transportation was used for commuting by the respondents and whether the respondents were working from home during the selected weeks. The NVP data can then thus be used to derive the modal split and teleworking numbers for each of the selected weeks and to analyse the difference between these selected weeks. Moreover, a distinction between blue- and white-collar workers have been made to find the difference in working from home and mode choice between people with physical and non-physical jobs.

4.4. Analysing individual characteristics affecting working from home

Whether people are going to telework strongly depends on individual characteristics. The relationship between individual characteristics and teleworking is examined with regression analyses. These individual characteristics regard demographics, such as age, income, job and living location and commuting distance. The acquisition and preparation of the data on these individual characteristics are respectively discussed in chapters 4.1 and 4.2. To examine which characteristics influence teleworking, three separate regression analyses are performed. Censored regression is used for two different analyses. Firstly, the impact of individual characteristics on telework rates in the period after the restrictions were lifted is assessed. Moreover, a censored logistic regression analysis was performed to determine the effect of characteristics on the change in telework behaviour between the beginning of the pandemic and the times when the governmental measures were lifted. The last regression is a multinomial logistic regression which determines the relation between the individual characteristics and the mode choice.

4.4.1. Censored regression analysis

Censored regression analyses are performed to determine both which people have a preference to work from home and which people changed working from home. In both cases, the dependent variable has a lower and upper threshold, for which censored regression is suitable. The dependent variable working from home preference lies between zero and one while the dependent variable change is expressed with a value between minus one and one.

In both analyses, the dependent variable has thus an upper and lower boundary, which cannot be exceeded and therefore, a simple linear regression cannot be used. In censored regression models these boundaries are censored and can therefore not be exceeded. The formula of a censored regression is the same as other regression models and can be found below:

$$y_i = x_i\beta + \varepsilon_i$$

Equation 1 - Regression model

However, the following conditions are in place;

$$y_i = \begin{cases} a & if\ y_i \leq a \\ y_i & if\ a < y_i < b \\ b & if\ y_i \geq b \end{cases}$$

Equation 2 - Conditions censored regression

Where a is the lower boundary and b the upper boundary of the dependent variable. For the change in working from home a and b are respectively -1 and 1, while these are 0 and 1 for the preference to work from home. When the censored regression model predicts a value beyond the threshold, the value is adjusted to either the lower or upper boundary.

4.4.2. Multinomial logistic regression analysis

Moreover, data analysis was performed to analyse which transportation mode people use to commute based on their characteristics. To include both teleworking and mode choice in the data analysis, teleworking is added to the choice of transportation modes. This means that people have the option to choose between car, public transport, bicycle, walking and teleworking. If the data analysis shows a relationship between individual characteristics and teleworking and mode choice, these individual characteristics can be used to determine the probability that a person or segment of the population is going to telework or which mode they choose for commuting.

Multinomial logistic regression analysis is used to determine the impact of individual characteristics on teleworking and mode choice probabilities. Logistic regression is a technique to determine the probability of a categorical dependent variable to happen based on the input independent variables.

When there are more than two possible outcomes of the dependent variable, a multinomial logistic regression should be used.

Since the data analysis is performed over timespans of a week, individuals might have made multiple commuting trips. Therefore, the regression analysis is performed for working days rather than for individuals. It should be noted that a multinomial logistic regression does not deal with multiple records of one individual and can therefore return biased results due to multiple working days by one respondent. A mixed or nested logit model would both be a better regression analysis, however, these cannot deal with a large amount of individual-specific independent variables compared to alternative-specific variables.

Multiple logistic models are created which can determine the probability of one of the five modes (car, public transport, bicycle, walking and teleworking) being used for a commuting trip given the individual characteristics of the person making the trip. To perform the multinominal regression analysis, a dependent variable and independent variables have to be determined. In this case, the dependent variable is mode choice and has five categories: car, public transport, bicycle, walking and teleworking. The independent variables are thus the individual characteristics that are present in the NVP and survey data and are listed in section 4.4.2.1. For the dependent variable, there are a total of K = 5 categories of which 1 = car, 2 = bicycle, 3 = walking, 4 = public transport and 5 = teleworking. Four (K-1) binary logistic models are created for the multinominal logistic regression, which each model the probability that a person chooses a mode relative to choosing teleworking (which is the baseline) for a commuting trip. These models are expressed as follows for k = 1, 2, 3, 4 (car, bicycle, walking and public transport):

$$\ln\frac{P(Y=k)}{P(Y=K)} = \alpha^{(k)} + {\beta_1}^{(k)} x_1 + \cdots + {\beta_n}^{(k)} x_n$$

Equation 3 - Multinomial regression model

In which:

$P(Y=k)$	= the probability of Y occurring for category k
Y	= independent variable with K categories
$x_1 \dots x_n$	= dependent variables
${\beta_1}^{(k)}$	= parameter of the dependent variable for category k
$\alpha^{(k)}$	= intercepts for category k

Not every characteristic might influence the probability of teleworking and the factors that do not significantly influence the teleworking probability are therefore removed as independent variables. The selection of the variables will be explained in paragraph 4.4.2.1. To determine the probability that teleworking will be replaced by a commuting trip made by car, bike, walking, or public transport, the following equation can be used:

$$P(Y=k) = \frac{e^{({\beta_0}^{(k)} + {\beta_1}^{(k)} x_1 + \cdots + {\beta_n}^{(k)} x_n)}}{1 + \sum_{j=1}^{K} e^{({\beta_0}^{(j)} + {\beta_1}^{(j)} x_1 + \cdots + {\beta_n}^{(j)} x_n)}}$$

Equation 4 - Equation to calculate the probability of a commuting trip

This model can thus determine the probability of a person choosing a mode of transportation for the modes car, bicycle, walking and public transport. The probability of a person going to telework is then:

$$P(Y=K) = 1 - P(Y=1) - P(Y=2) - P(Y=3)$$

Equation 5 - Equation of teleworking probability

The multinomial logistic regression analysis results in multiple regression models that estimate the probability that a person will choose a transportation mode for commuting given the sociodemographic characteristics of the person. Since different weeks during the pandemic are analysed, a multinomial logistic regression analysis is performed for multiple periods.

4.4.2.1. Variable selection

Before using the model, it should include the best possible subset of variables which provide the best fit for the model. In order to find the best possible selection of variables, backward elimination is applied. This method starts with fitting the model with all the predictor variables. The predictor variable with the lowest significance is removed from the subset and the model is fitted again. This step is repeated until the subset of variables that provide the best model fit is reached. The variables that remain, will be used in the final model.

4.5. Implementing the regression model into the model of Almere

During the data analysis, data is gathered on teleworking during the COVID-19 pandemic and individual characteristics influencing this. Moreover, a multinomial logistic regression analysis was performed which resulted in logistic regression models that can be used to estimate the probability that a person chooses a certain mode of transportation for commuting.

The section starts with a brief introduction to the OmniTRANS model Almere, which is used during this research. The subsequent paragraphs explain how the results of the regression analysis are implemented in the model of Almere and which results are extracted from the model.

4.5.1. Model Almere

As stated before, the OmniTRANS model Almere is used in this research to model the possible effects of teleworking on commuting patterns. In this section, this model will be explained briefly to give an overview of its possibilities. The information about the model is retrieved from the technical report of the model (Possel & Herder, 2019).

The model Almere is multimodal and includes several travel motives. During this research, the modes car, public transport, and bicycle are going to be used in the model. Additionally, teleworking (thus staying at home) will be added as the fourth mode of transport. In this way, the mode shift from any mode of transport to teleworking can be modelled. In this research, this will be done for the motive work.

In the multimodal traffic model Almere a classic four-step model is used, which thus performs four steps to model the traffic for Almere and its surroundings. The four steps are visualised in Figure 4. In the first step, the model generates trips for each zone based on the purpose of the trips. These trips are distributed to the destinations in the second step. In the third step, which is executed at the same time as step 2, the modal split is calculated for these trips. The last step includes the assignment of the trips to routes on a network.

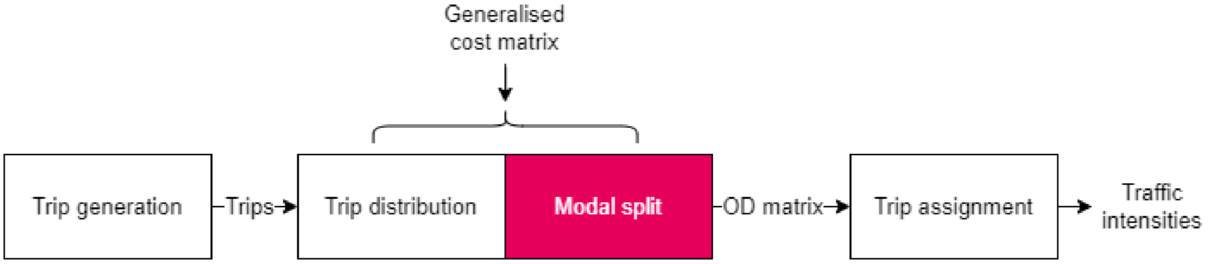

Figure 4 - Four-step model, used in traffic model Almere

For the second and third step, a gravity model is used. The model Almere has 1400 zones including zones within and multiple influential zones outside Almere. These influential zones include cities like Amsterdam, Utrecht, Amersfoort and Zwolle. Based on socio-economic data, the number of departures and arrivals generated for each zone can be determined. A gravity model uses production factors for origin and attraction factors for destination locations. In this case, the production and attraction factor for home as origin or destination is the total employed population living in the zone. For work, the production and attraction factor is the total number of jobs within a zone. To determine the number of trips between the zones, the resistance is calculated. The resistance (or costs) between two zones is dependent on the travel time and the travel distance between the zones and can be calculated with the following equation:

$$K_{mp} = L_m * VoD_{mp} + R_m + VoT_{mp}$$

Equation 6 – Generalised cost equation

In which:

K_{mp} = generalised cost for modality *m* and motive *p*

L_m = distance (km) for modality *m*

VoD_{mp} = Value of Distance for modality *m* and motive *p*

R_m = travel time (hours) for modality *m*

VoT_{mp} = Value of Time for modality *m* and motive *p*

The generalised costs to travel between two zones differs thus per modality and motive. The model makes trade-offs between the willingness to reach the destination and the costs of travelling. By doing this, the model ultimately determines the number of trips from which zones to which zones with which transportation mode. This is then stored in an Origin-Destination Matrix (OD matrix) per mode of transportation. The model Almere works with the base year 2017 which will also be adjusted in this research to perform analyses.

4.5.2. Adjusting the model

To calculate the effects of teleworking on commuting patterns, the model of Almere is adjusted. In the previous, section it is explained that the model of Almere is a four-step model, however, only the calculation of the model split is adjusted in this research. This step is highlighted with a pink colour in Figure 4. The trip generation, distribution and assignment are kept thus same during the research. In this way, the effects of the calculated changes in the modal split, due to the inclusion of teleworking, can be directly seen in the results of the model.

During the data analysis phase of this study, a regression model is generated which can predict the probabilities that a person uses a certain modality for commuting or that they perform their work from home. This regression model can be used as input for the model of Almere to recalculate the modal split for the trips between each origin-destination pair of zones. In order to calculate the modal split, the regression model uses the characteristics of the person, his home and job location and the characteristics of the trip.

The model of Almere, however, does not have information on the individual level, but on the zone level. In the regression model, a large part of the independent variables expects a binary value, which is often not present on the zone level in the model of Almere. For the most independent variables, the model of Almere has absolute numbers, which can be used to calculate the percentages of each category per independent variable. For example, the percentage of people that own a car or that received medium education can be calculated. When filling in the calculated percentages, the regression model still gives a result. By filling these percentages instead of a 0 or 1, a linear relationship between the dependent and the independent variable is assumed, although this is not the case for most of the independent variables. A solution to prevent the assumption of linearity between independent and dependent variables is to simulate the population. This will result in a synthetic population for each of the zones in which persons get assigned characteristics based on which characteristics are present in the zone. A simulation would thus be an ideal option if a simulation was not so time-consuming. Since the regression model needs information from the inhabitants (origin zone), their jobs (destination zones) and the trip between the origin and destination zone, the population should not only be simulated for each of the 1400 zones, but for all the origin-destination pairs. It has therefore been decided to leave the simulation of the population outside the scope of this study and use the data on a zonal level, and thus assume linearity between the independent and dependent variables. To see whether these results deviate (too) much from the results when performing a simulation of the population, a sample of origin-destination pairs has been selected for which the population is simulated manually.

In the data analysis section, the effects of individual characteristics on teleworking and mode choice have been determined for four periods, however, only the regression model calculated for the period after the pandemic is used in the model of Almere because this model gives the most realistic post-COVID effects of teleworking on commuting patterns.

Instead of working with individuals, the gravity model of Almere makes use of zones that contain the average characteristics of the inhabitants of these zones. Moreover, the model already contains per zone the number of outgoing and incoming trips. In the section Model Almere, it has been described that the numbers of trips are stored in an OD matrix. By using the logistic regression models, it can be determined which proportion of the trips will be replaced by teleworking and which proportion of the trips will be made by car, public transport and bike. These estimated proportions are then adjusted in the OD matrix to determine the new number of commuting trips for each mode of transport based on the proportions that are calculated using the logistic regression models. The proportions are based on the characteristics of zones and thus differ per OD pair depending on the inhabitants of the origin zone, the job locations at the destination zone and the trip length between the two zones.

4.5.2.1. Variables model

Table 4 - Independent variables used in the model of Almere

Independent variable		Data source
Travel time by car		OmniTRANS model
Age		Mobiliteits-spectrum
Gender		
Education level		
Urban density of living location		
Household size		
Household composition		
Driver's license		
Car ownership		
Sector	Industry	
	Healthcare	
Function	Office	
	Education	
	Already teleworking	
Education level		CBS (2021)
Accessibility of job location		Calculated*

The regression model on the influence of individual characteristics on mode choice is implemented in the OmniTRANS model of Almere. The regression model can calculate probabilities for teleworking and the transportation modes between each origin zone and destination zone. In order to calculate these probabilities, the model needs independent variables, such as characteristics of people, their jobs and their commuting trip. Although the model of Almere includes already data for each zone and data on travel times between the zones, not all needed data is present. Therefore, additional data is gathered from other data sources to include as much as possible data in the OmniTRANS model. From the data available in the model of Almere, only the travel time by car was used. This is because the Mobiliteitsspectrum contained often more detailed and therefore more accurate data on the same variables. Moreover, the Mobiliteitsspectrum was also used to gather additional data for the model.

Both education level and accessibility for job location were not available in either the OmniTRANS model or the Mobiliteitsspectrum and are therefore retrieved from other sources. CBS contains a lot of information on the characteristics of areas in the Netherlands as well as the education level. The number of people per education level in each PC4 code has been retrieved and aggregated to the zones in the Almere model. In paragraph 4.2.3 it was explained that the accessibility of the job location is calculated by dividing the number of people that can reach a location by their travel time. This calculation is also performed in OmniTRANS to get the accessibility per zone. The travel time and the number of inhabitants of each zone are used as input for this calculation.

4.5.3. Analysing the effects of teleworking on commuting patterns

By implementing the regression model in OmniTRANS, the model split will be recalculated and developments in traffic intensities in the network of Almere will be generated. The effects of teleworking on mobility are going to be assessed by four criteria. These assessment criteria are traffic intensity, modal split, congestion and travel times between Almere and its surrounding cities.

By assessing the traffic intensity in the model and comparing it with the traffic intensity before the implementation of teleworking into the model, increases and decreases in traffic intensity can be seen. These differences in traffic intensity are projected on the network, which enables an overview of where the biggest contrasts in traffic intensity are located. It is expected that teleworking has a traffic intensity-reducing effect. Decreases are expected especially in the (morning) rush hour and on work routes (access roads and near job locations). Moreover, the differences in intensity are assessed for traffic within Almere and for in- and outgoing traffic. Since Almere inhabits many people that work outside Almere, mainly in Amsterdam, it is expected that the biggest decreases are visible in the intensities of traffic entering or leaving Almere. Especially in the morning rush hour, a significant decrease in outgoing traffic is expected.

Secondly, the modal split is assessed. The modal split tells how the usage of the mode of transportation is divided for commuting trips. By assessing the modal split in each scenario, the effects of teleworking on mode choice can be assessed. Due to the increase in teleworking, a decrease in all other modes is expected.

Traffic intensities are the main cause of congestion, and therefore congestion on the network of Almere is also assessed by looking at the Intensity-Capacity ratio on the links in the network. A reduction in traffic intensities is expected and therefore also a decrease in congestion is anticipated.

The last assessment criterium is the travel times between Almere and its surrounding cities. Almere is located close to Amsterdam and therefore a good residential location for commuters with a job in Amsterdam. The increase in teleworking would make Almere an even more interesting location to live. Moreover, the cities Utrecht, Zwolle and Harderwijk are also located near Almere. The travel times between Almere and these cities are analysed. Reductions in travel times between Almere and the surrounding cities as a result of the increase in teleworking are expected. The highest decreases are expected between Almere and Amsterdam.

5. Data analysis results

In the previous section, it has been explained that data analysis is performed to determine the effects of individual characteristics on the probability that a person is going to work from home. In this chapter, four different analyses will be performed of which the first data analysis is performed to answer the first research question. In this data analysis, the development of teleworking during the COVID-19 pandemic is analysis. The other three data analyses contribute to answering research question two. In all three cases, a regression analysis has been performed to find correlations between individual characteristics and the probability of working from home, the change in probability and mode choice. For the first two, a censored regression analysis is used, while a multinomial regression analysis is performed to find the influence of individual characteristics on mode choice. This chapter consists of two parts of one paragraph each. Paragraph 5.1 presents the results of the development of teleworking in the Netherlands during the pandemic and contributes to answering research question one. In Paragraph 5.2, the results of the data analysis on the impact of individual characteristics on teleworking are presented.

5.1. COVID-19 pandemic in the Netherlands and its influence on teleworking

In this thesis, the effects of teleworking on commuting patterns are examined. Although working from home existed much longer, teleworking numbers increased firmly during the COVID-19 pandemic. Before looking at the effects of teleworking on commuting patterns in the Netherlands, it is interesting to examine how teleworking has developed in recent years, during different intensities of the COVID-19 pandemic.

5.1.1. Teleworking numbers

As has been explained in paragraph 4.2.1, a selection of weeks during the period between February 2020 and May 2022 was made to reduce the amount of data. The intensity of the COVID measures differentiated during this period from no measures at all to a severe lockdown. The selection contained therefore different weeks in which varying advices to work from hone were applied. In this thesis, four levels of this advice have been identified. When the government did not give any advice on working from home, level 0 is applied. Level 1 implies a light working from home advice, where people can work from home if this is possible, while level 2 means that the government advised working at least half of the time from home. In situations where the infection rates were at its peak, the government urged people to work from home, which is here categorised as level 3 (Rijksinstituut voor Volksgezondheid en Milieu, 2021). For each of these levels, weeks have been selected.

The analysis resulted in teleworking numbers for each of the selected weeks. When comparing the number of teleworking days to the total number of total working days, the working from home percentage can be calculated. The working from home percentage per week can be found in Figure 5, which also includes the teleworking advice.

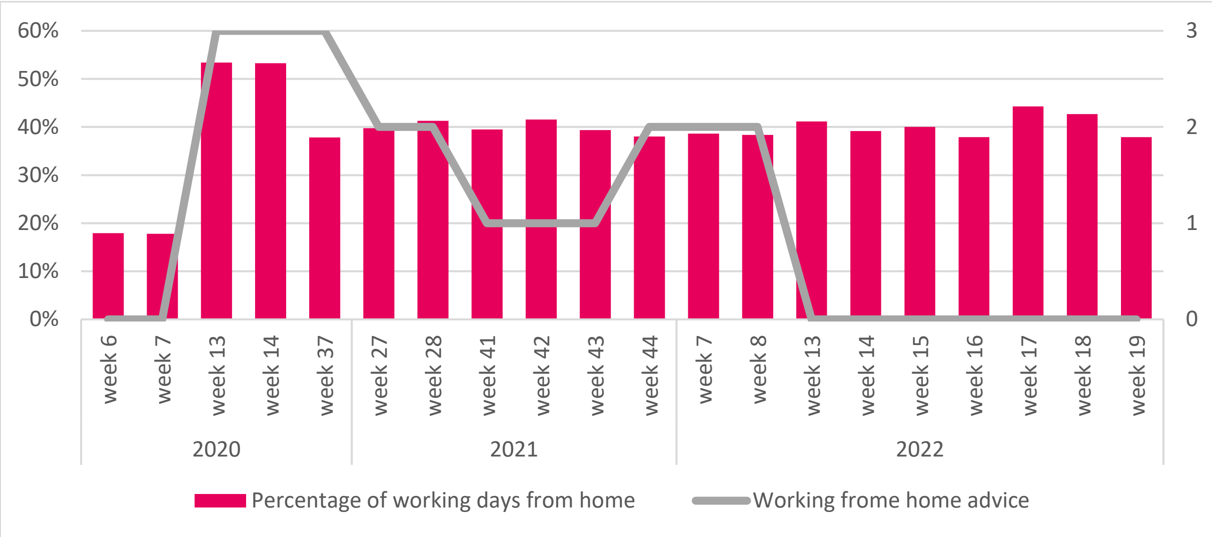

Figure 5 - Percentage of working days from home versus the working from home advice

When looking at this graph, a few things can be noted. At the beginning of the pandemic, a steep increase in teleworking rates can be observed. Where before the pandemic the teleworking rates were fewer than 20%, this increased to over 50% during the first weeks of the pandemic. This is also in line with the increase in the working from home advice, which was at its highest at the time. In the theoretical framework (paragraph 3.1) the results of a study by De Haas, Faber and Hamersma (2020) were presented. This study showed similar, however a little lower, statistics regarding teleworking. This research conducted a survey in which 44% of the respondents indicated to start working from home or to work from home more, while 39% worked more than 75% from home. Weeks later, the teleworking rates decreased to around 40%, while the advice to work from home remained at level 3. In the following selected weeks, which were spread over the two years after the beginning of the pandemic, the teleworking rates stayed around 40%. This is remarkable since the working from home advice differentiated firmly during these weeks. Even in the weeks when the advice was lifted completely, the working from home rates did not drop. It thus seems that the pandemic was an initiation for people to start teleworking, while after the pandemic, many people still kept working from home, despite the advice to work from home being lifted. Research conducted by the Ministry of Infrastructure and Water Management amongst 1,100 companies during the pandemic already concluded that working from home is a ‘keeper’. Almost all participating companies indicated that they want to invest more in teleworking (Rijksoverheid, 2021).

5.1.2. Mode choice

According to the findings in the previous paragraph, the COVID-19 pandemic had a positive influence on teleworking numbers. The increase in teleworking implies also a decrease in the number of commuting trips. To find out which transportation modes experience a decline due to teleworking, the modal split is determined. For the modal split, a distinction has been made between the modes of car, bicycle, walking, public transport and teleworking. Teleworking is included as a new mode of transportation (although it is not a transportation mode). An overview of the share of trips made by each transportation mode throughout the whole dataset can be found in Figure 7.

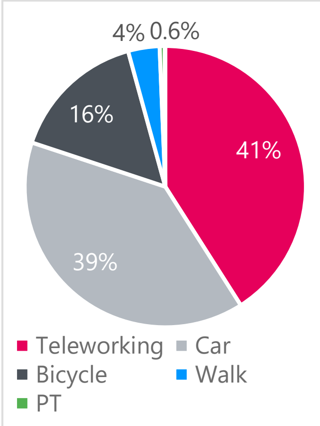

Figure 7 - Share of work-related trips made per mode in the data

The modal split of the NVP panel members is also analysed per selected week to see developments in the use of the transportation modes during the analysed period. Since the number of participants differentiated over the selected weeks, the modal split per week is expressed as the mean number of commuting trips that a person makes in a week with that transportation mode. The modal split in the selected weeks, expressed as a mean number of trips per person per week, is depicted in Figure 6.

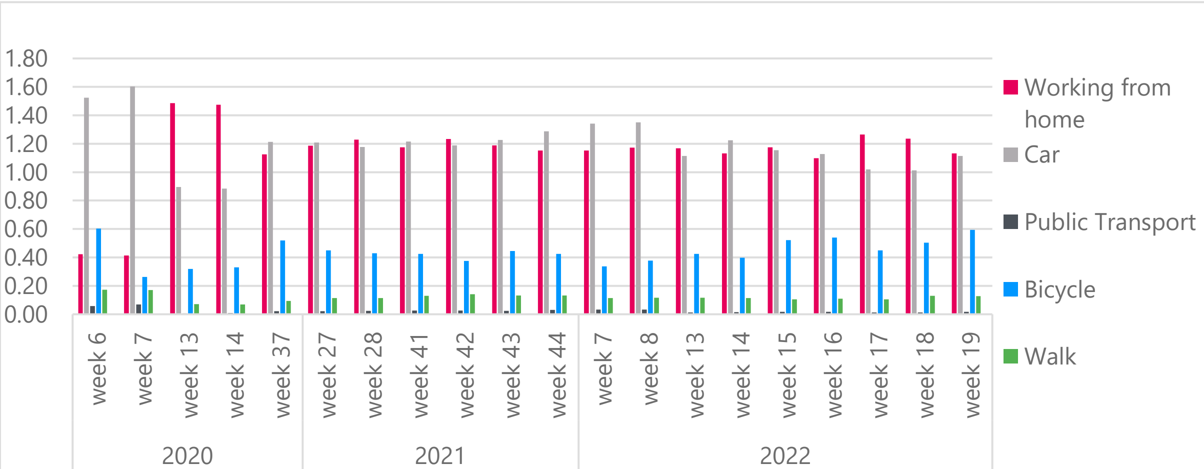

Figure 6 - Mean number of days per mode of transportation

The modal split for each of the twenty selected weeks is thus shown in Figure 6 and can be analysed. The teleworking rates are in line with the results in Figure 5. However, this figure also gives an insight into the use of different modes of transport throughout the pandemic. In the weeks prior to the pandemic, the NVP panel members predominantly used the car for commuting. On average, respondents commuted 1.5 days per week by car. Other modes are used less often in these weeks. Due to COVID-19, teleworking increased at the expense of other modes of transportation. Especially in the first weeks of the pandemic, a shift from all commuting modes to teleworking can be seen. Later during and after the pandemic, teleworking rates dropped slightly and car, cycling, and walking numbers increased again. However, the average number of days per week for these modes is still below the pre-COVID level and stayed at this level until May 2022. When looking at public transport, the level of usage did not recover since the start of the pandemic. It should be noted that the share of public transport trips in the NVP data is rather small and can thus be under-represented.

Figure 6 gave an insight into the modal split and how this has changed during and after the pandemic. Although decreases and increases could be seen for some of the modes, it remained unclear among which modes the changes were. A Sankey diagram has been created to depict the underlying changes between the modes of transportation and it can be seen in Figure 8. The bars on the left side of the figure show the modal split before the pandemic, while the bars on the right side represent the modal split post-COVID (May 2022). The lines between the bars indicate the changes between each mode. The sizes of the bars and the lines respectively correspond to the percentage of trips made per mode and the percentage of trips that changed between the two modes of transport.

As observed earlier in this report, the pandemic caused people to work from home, even after the measures were lifted. This can also be seen in the Sankey diagram, where there is a significant increase in working from home. Each mode of transportation experiences a decrease, from where the largest part is switched to working from home. The use of public transport disappears almost completely due to the increase in working from home.

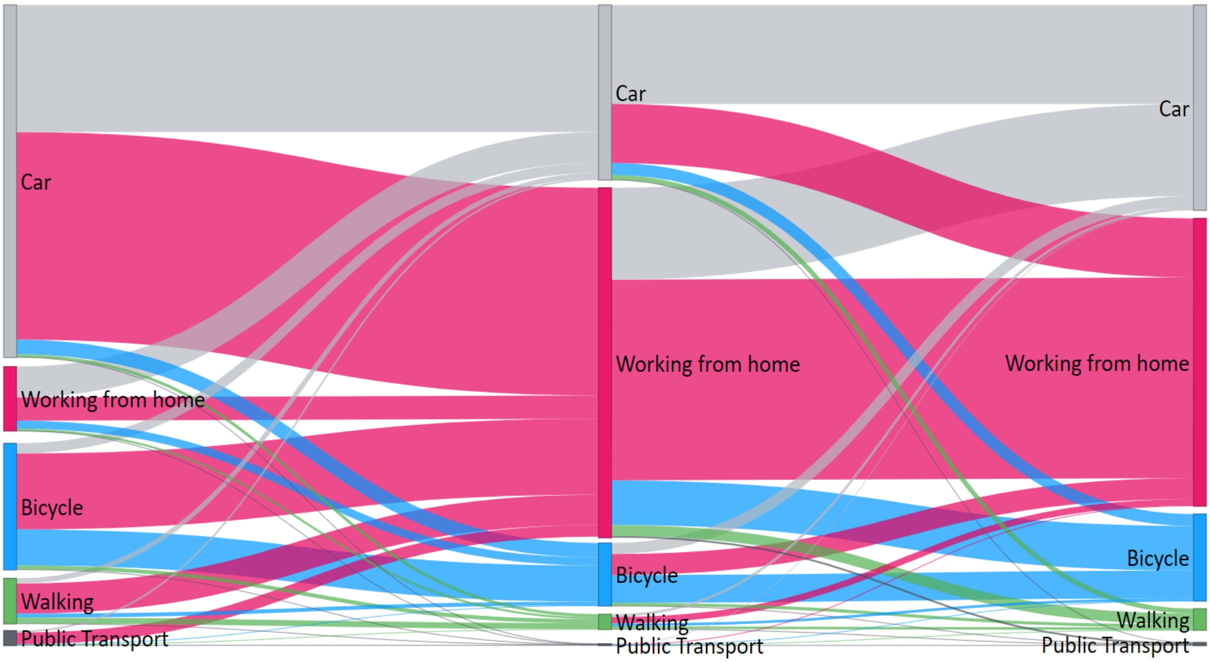

Figure 8 - Sankey diagram. Represents the shift in mode choice among the NVP panel members (left = pre-COVID, middle = during COVID, right = post-COVID)

It is surprising to see a significant flow from working from home before COVID to the use of car and bicycle after, however, this is due to the determination of working from home before the pandemic. This was based on people who did not commute before but after the pandemic. With this in mind, the flow from working from home to car and cycling can be explained.

Furthermore, a note should be made on another assumption that was made to get the Sankey diagram. The NVP data was used as input for the Sankey diagram, and since this data only contains the information on the trips and the mode used for these trips, the change in mode choice had to be obtained in another way. The number of trips per mode per person before and after the pandemic was thus known and can be used to determine the flow between the modes. The percentages of trips a person made per mode before and after the pandemic were calculated and could be used to find the flows.

5.1.3. Blue- vs. white-collar jobs

To get a better overview of who is working from home, the respondents will be split up into three categories, blue-collar, white-collar and other. Blue-collar workers are employees that do heavy physical work at a low salary. Jobs which are often not physical and for which high education is needed are called white collar jobs (Melissa Parietti, 2022). In this thesis, people with function production are seen as blue-collar workers while people working in office, education, administrative, research and management functions are called white-collar workers. Jobs in healthcare, field service and other fall in between the blue and white collar and are therefore not included in this analysis. For blue- and white-collar jobs, the modal split per week is shown in respectively Figure 9 and Figure 10. To ease the comparison of the two graphs, a combined graph is presented in Appendix I.

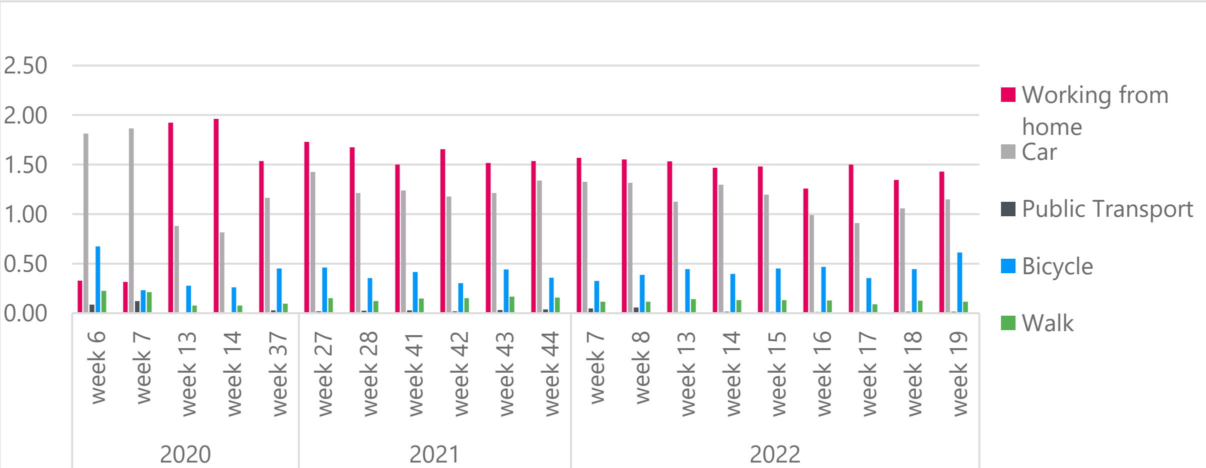

Figure 9 - Mean number of days per mode of transportation: White-collar workers

The number of days working from home seems to be higher among white-collar workers. On average, white-collar workers worked 1.5 days from home at the start of the pandemic and between 1 and 1.2 days in later weeks, while the white-collar workers worked respectively around 2 and 1.5 days from home. Moreover, the percentage of days working from home was also higher for white-collar workers. From these results, it can thus be concluded that white-collar workers tend to work from home more than the average. The number of days working from home seems to be higher among white-collar workers. On average, white-collar workers worked 1.5 days from home at the start of the pandemic and between 1 and 1.2 days in later weeks, while the white-collar workers worked respectively around 2 and 1.5 days from home. Moreover, the percentage of days working from home was also higher for white-collar workers. From these results, it can thus be concluded that white-collar workers tend to work from home more than the average.

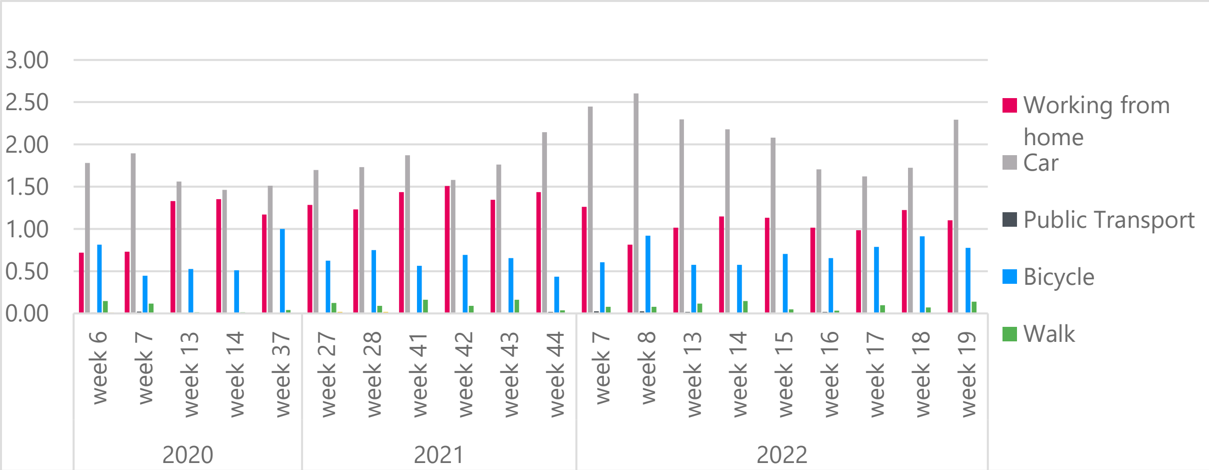

Figure 10 - Mean number of days per mode of transportation: Blue-collar workers

In contrast to white-collar workers, blue-collar workers tend to work from home less than average. In Figure 10, car use is the favourite mode of transportation for commuting among the blue-collar workers throughout all of the selected weeks. Especially pre-COVID and in 2022, the car was much more often used than other modes of transportation and working from home. Although the preference for cars, working from home is also common among blue-collar workers, which is remarkable because their jobs can often not be done from home. A few explanations for these results can be found.

Assumptions were made on if a person was working from home based on whether they were working in the reference week. If persons made fewer trips during a week compared to the reference week it was assumed that they were working from home. This could lead to incorrect assignment of working from home in cases of dismissal, illness, vacation, or retirement. Moreover, the COVID-19 pandemic caused companies to close for a certain period. Especially at the beginning of the pandemic, some factories were closed or scaled down, forcing the employees to stay home (UWV, 2020).

Furthermore, bicycle use is relatively high among blue-collar workers. All in all, blue-collar workers are going more often to their work than the average respondent. This is not surprising, as they often must be physically present to perform their job.

When analysing this result, the following should be noticed. Whereas white collar workers were well-represented in the NVP panel, blue collar workers were not. Among the 2827 included respondents, only 96 had a blue-collar job. This could thus lead to more variable results and even misleading conclusions.

5.2. The impact of individual characteristics on teleworking

To make predictions on the impact of teleworking on commuting patterns, it should be known which people are teleworking under what circumstances. In this research, the NVP data has been analysed to determine which people were working from home and which characteristics influence the choice to work from home. To find the impact of individual characteristics on teleworking, three different regression analyses are performed. These regression analyses estimate respectively the impact of individual characteristics on the probability that a person goes teleworking after the pandemic, the impact of individual characteristics on the change in teleworking between the start of the pandemic and after the pandemic, and the impact of individual characteristics on their mode choice after the pandemic.

Before diving into the regression analysis results, it will be clarified how the regression results should be interpreted. The results of each regression are presented in a table. For each of the independent variables, the table contains an estimated coefficient, a standard error, and a p-value. These can be interpreted as follows. The estimated coefficient explains the influence of the independent variable on the dependent variable. Since this influence is estimated based on patterns visible in the data, it can be uncertain in several cases. The standard error measures the uncertainty of the estimated coefficient and can be used to determine the p-value for the independent variable. To determine whether the estimated coefficient has a significant impact on the dependent variable, the p-value should be considered. The p-value shows the probability of obtaining the observed results with the estimated coefficient. A lower p-value indicates a higher statistical significance of the observed difference. During this research, it is assumed that when an independent variable has a p-value below 0.05, its estimated coefficient is statistically significant. However, also estimated coefficients with a slightly higher p-value are also evaluated.

Several regression analyses are thus performed in this chapter and different datasets with varying independent variables are used as input. It is important in each case the independent variables are not too strong correlated because this can result in variables that are over-represented. To ensure high correlations between the independent variables do not occur, the correlations are analysed in Appendix II. This analysis resulted in no alarming correlations between the independent variables for all of the regression analyses.

Together, the estimated coefficients of the independent variables form a regression model. These regression models can be used to calculate the dependent variable based on the independent variables. Several regression models are created during the research. The first regression model can be used to determine the probability of a person working from home after the pandemic, based on their characteristics. The change in probability of working from home can be estimated using the second regression mode. Both are censored regression models and their results are presented in respectively paragraphs 5.2.1 and 5.2.2. Furthermore, a multinomial regression model is determined that uses individual characteristics to determine the mode choice. In paragraph 0, regression models are presented for different clusters of weeks.

5.2.1. Probability to work from home after the pandemic

During the COVID-19 pandemic, many employees were forced to work from home, either by the measures taken by the government or by their employer. However, the measures of the government are no longer in place and employers often welcome their employees back to the workplace. In many jobs, employees are thus no longer forced to work from home and can make their own decision to work from home. Although some jobs must be performed from the workplace, the data from the weeks after the measures were lifted could be used to find out which persons have a preference to work from home and determine the probability of one working from home based on their characteristics.

As explained in chapter 4.2.2, the number of days working from home and the number of days commuting per week has been decided for each of the respondents. This information was used to determine which percentage of the working days people were working from home in each of the weeks. In this step of the research, it is researched who is working from home in the period after the pandemic, and therefore, the percentage of days that people were teleworking is calculated for the weeks 13 to 19 in 2022, in which the working from advice was lifted. To determine which characteristics influence the probability that people are working from home, a censored regression analysis is performed. In this regression analysis, each respondent is an observation which has thus a percentage of days that they work from home. This percentage of days working from home is the dependent variable. The characteristics of the respondents serve as independent variables and are selected in paragraph 4.2.3. The censored regression analysis determined for each independent variable the influence on the dependent variable and these results can be found in Table 5.

However, the effects of many of the variables have a p-value over 0.05, which means that they are not considered to be significant. Although independent variables with a p-value over 0.05 are not statistically significant, independent their coefficients can still be used to make conclusions on their influence on the probability that a person works from home. In just eleven cases the p-value is below 0.20, meaning that there is a confidence interval of 80%. Only the coefficient of the variables where this is the case will be analysed since the other coefficients are not significant.

The first somehow significant variable is industry. A negative correlation of -0.178 on the working from home percentage can be found in the table behind the variable industry. This means that a person who has a job in the industry sector is less likely to be working from home. If a person works in the industry the working from home percentage is expected to drop by 17.8 per cent. This makes sense because industry workers often cannot perform their jobs from home. Healthcare has an even higher negative correlation with working from home and this can also be explained since healthcare workers should often be present at their workplace to perform their work. Unlike industry and healthcare workers, people who have an office function are more likely to work from home. An office job is in most cases particularly suitable to be done from home. The resulting negative correlations between working in the sectors industry and healthcare and the probability of teleworking are in line with the findings of De Haas, Faber, & Hamersma (2020) and Belzunegui-Eraso & Erro-Garcés (2020) that are presented in chapter 3.2.1. These findings also conclude the positive relationship between working in an office and teleworking.

Table 5 – Censored regression results; probability working from home

	Variable	Estimate	Std. Error	Pr(>t)	
	intercept	-0.021	0.458	0.963	
	travel time by car in hours	-0.121	0.129	0.349	
Sector	industry (ref = no)	-0.178	0.110	0.104	
Sector	construction (ref = no)	0.248	0.201	0.217	
Sector	ICT (ref = no)	0.040	0.113	0.723	
Sector	healthcare (ref = no)	-0.198	0.103	0.054	.
Function	office (ref = no)	0.140	0.086	0.104	
Function	management (ref = no)	-0.088	0.122	0.468	
Function	research (ref = no)	-0.231	0.298	0.438	
Function	education (ref = no)	0.038	0.157	0.806	
Reason	government (ref = already working from home)	0.052	0.071	0.464	
Reason	employer (ref = already working from home)	0.070	0.069	0.311	
Reason	commuting not nice (ref = already working from home)	0.319	0.131	0.015	*
Pleasure	little less (ref = much less)	-0.162	0.151	0.147	
Pleasure	about the same (ref = much less)	0.012	0.112	0.919	
Pleasure	little more (ref = much less)	-0.171	0.116	0.259	
Pleasure	much more (ref = much less)	-0.079	0.185	0.669	
Productivity	little less (ref = much less)	0.260	0.137	0.043	*
Productivity	about the same (ref = much less)	0.157	0.129	0.222	
Productivity	little more (ref = much less)	0.228	0.128	0.097	.
Productivity	much more (ref = much less)	0.170	0.148	0.251	
	higher education (ref = lower education)	0.249	0.280	0.375	
	medium education (ref = lower education)	0.061	0.278	0.826	
	modal to two times modal (ref = lower than modal)	-0.153	0.146	0.294	
	two times modal or more (ref = lower than modal)	-0.179	0.152	0.238	
	age	0.004	0.003	0.289	
	gender (ref = female)	-0.096	0.068	0.159	
	high density (ref = low density)	-0.173	0.087	0.046	*
	medium density (ref = low density)	-0.268	0.104	0.010	*
	driver's license (ref = no)	-0.063	0.219	0.775	
	car ownership (ref = no)	0.064	0.126	0.614	
	household size	0.005	0.044	0.909	
House hold	adult (ref = single)	0.177	0.110	0.109	
House hold	with children (ref = single)	0.083	0.150	0.580	
	Accessibility of job location	0.027	0.028	0.333	
	logsigma	-0.701	0.056	0.000	***
	Number of observations	306			
	Loglikelihood	-248.966			

A positive relationship was also found between not liking commuting (with respect to already working from home) and teleworking. This means that people that indicated during the survey that they do not like commuting are more likely to work from home post-COVID than people who worked already from home even before the pandemic. It might thus be that people that were forced to work from home during the pandemic saw the opportunity to avoid commuting by working from home and are therefore often working from home even when they are no longer forced to work from home.

The pleasure and productivity variables explain the pleasure and productivity the respondent experienced while working from home in comparison to working at the workplace. For both variables, the categories are all with respect to the category much less. Almost all of these categories have a negative correlation with working from home and since they are all in respect to much less, the variable much less pleasure has a positive impact on working from home. Persons who experienced much less pleasure working from home during the pandemic are thus expected to work more from home than persons that experienced more pleasure. It should be noted however that the p-values of the categories are predominantly high which means that the estimated coefficient is not statistically significant. For productivity, a positive correlation between all the categories higher than much less productive and working from home can be seen. This means that a person who experienced being more productive while working from home is more likely to work from home post-COVID.

The coefficient for medium and high density is estimated with respect to low density and returns in both cases a negative value. It can thus be concluded that people living in low-density areas are expected to work from home more often than their counterparts living in higher-density areas. Bastiaanssen, Johnson, & Lucas (2021, p. 307) cited the following about residents of low densely populated areas: "People residing in less densely populated peripheral and rural regions typically commute over longer distances due to the paucity of nearby jobs, while trips made in urban regions are relatively short".

For people living in lower-density areas, it is thus often harder to access jobs and therefore it is not a surprise that people living in these areas are more likely to work from home. Lastly, living in an adult household (without children) has a positive correlation with the working from home percentage. The reference category of this variable is people living in a single household and this positive correlation can therefore be explained. According to Choi, et al. (2022), people living in a single household have a higher chance of being lonely and it is, therefore, likely to assume that they come more often to their workplace to increase their social interaction.

5.2.2. Change in teleworking behaviour

The first regression analysis pointed thus out which characteristics influence the probability that a persons is going to work from home. By comparing the percentage that people were working from home in the weeks after the pandemic to this percentage during the first weeks of the pandemic (week 13 and 14 of 2020), insight could be gained which people stopped, started, or kept working from home. In the first weeks of the pandemic, people were often forced to work from home, which was not anymore the case in the weeks after the measures were lifted. By looking at the changes in teleworking behaviour, it can be decided whether people were working from home because they were forced or that they prefer to work from home.

Also here, a censored regression analysis has been performed to determine the relationship between the selected variables and the independent variable. In this case, the independent variable is the difference in the individual percentage working from home days between the start of the pandemic and after all measures were lifted. The results of the regression analysis can be found in Table 6.

Like the previous regression analysis, the regression analysis between the individual characteristics and the change in working from home returned few significant results. Although many variables do not have a significant influence on whether people changed their working from home behaviour, several things can be inferred from these results.

The results of the variables of job function and sector showed almost all a decreasing impact on working from home between the start and the end of the pandemic. While it is no surprise that people started to work again because it is possible, not for every job a decreasing effect was expected. For

example, people working in ICT or in an office function might be more likely to continue or even

increase working from home than people in other jobs. Although the coefficients

of the sector and function variables do not reflect this, their impact is often not significant.

When looking at pleasure, a positive correlation between more pleasure and an increase in working from home can be seen. Especially people that indicated much more pleasure in working from home were more likely to continue or increase working from home after the pandemic.

Table 6 - Censored regression results; change in teleworking between the beginning of the pandemic and after the pandemic

	Variable	Estimate	Std. Error	Pr(> t)	
	intercept	-0.046	0.388	0.906	
	travel time by car in hours	-0.098	0.103	0.340	
Sector	industry (ref = no)	0.024	0.090	0.791	
	construction (ref = no)	-0.006	0.161	0.969	
	ICT (ref = no)	-0.054	0.091	0.557	
	healthcare (ref = no)	-0.099	0.084	0.242	
Function	office (ref = no)	-0.078	0.078	0.317	
	management (ref = no)	-0.160	0.103	0.121	
	research (ref = no)	-0.389	0.290	0.180	
	education (ref = no)	0.023	0.132	0.860	
Reason	government (ref = already working from home)	-0.068	0.060	0.253	
	employer (ref = already working from home)	-0.078	0.057	0.174	
	commuting not nice (ref = already working from home)	0.110	0.119	0.353	
Pleasure	little less (ref = much less)	0.097	0.133	0.315	
	about the same (ref = much less)	0.121	0.096	0.214	
	little more (ref = much less)	0.113	0.098	0.398	
	much more (ref = much less)	0.344	0.163	0.035	*
Productivity	little less (ref = much less)	-0.007	0.116	0.945	
	about the same (ref = much less)	0.038	0.109	0.723	
	little more (ref = much less)	0.098	0.107	0.394	
	much more (ref = much less)	-0.082	0.124	0.511	
	higher education (ref = lower education)	-0.424	0.240	0.078	.
	medium education (ref = lower education)	-0.463	0.238	0.051	.
	modal to two times modal (ref = lower than modal)	-0.070	0.125	0.576	
	two times modal or more (ref = lower than modal)	-0.086	0.129	0.507	
	age	0.008	0.003	0.007	**
	gender (ref = female)	-0.047	0.057	0.413	
	high density (ref = low density)	-0.091	0.071	0.200	
	medium density (ref = low density)	-0.106	0.088	0.229	
	driver's license (ref = no)	-0.035	0.182	0.850	
	car ownership (ref = no)	0.131	0.114	0.249	
	household size	-0.001	0.037	0.982	
Household	adult (ref = single)	-0.084	0.095	0.374	
	with children (ref = single)	-0.125	0.126	0.324	
	Accessibility of job location	0.035	0.023	0.126	
	logsigma	-0.991	0.048	0.000	***
	Number of observations	230			
	Loglikelihood	-105.678			

In the previous analysis, it became clear that after the pandemic, people with higher received education were more often working from home than people with lower perceived education. However, the results of this analysis indicate that higher educated people were more often found to decrease working from home than lower educated people.

According to this analysis, age has a positive correlation with the change in teleworking behaviour, meaning that older people are more likely to increase or maintain their habit to work from home.

Furthermore, people living in more densely populated areas decreased their working from home more often than the residents of less densely populated areas.

5.2.3. Mode choice

The third analysis is performed to find the impact of individual characteristics on the mode choice for commuting trips. The conventional modes car, public transport, cycling and walking as well as the additional mode working from home are included in this analysis.

The data selected in this research includes commuting trips from weeks before, during and after the pandemic. To determine the impact of individual characteristics on mode choice during different phases of the pandemic, four periods of clustered weeks were selected. The first period consists of the weeks before COVID. The first two selected weeks in the pandemic have also been defined as a period. Another period included all weeks during the pandemic. The last period contains all the selected weeks after the working from home measures were lifted. An overview of the selected weeks per period can be found in

Table 7. For each of the four selected periods, a multinomial regression was performed in which the influence of individual characteristics on mode choice is determined.

Table 7 – Periods used in regression analyses

Period	Weeks	Year
Before the pandemic	6 & 7	2020
First weeks of the pandemic	13 & 14	2020
During the whole pandemic	13 & 14	2020
	37	
	27 & 28	2021
	41 - 44	
	7 & 8	2022
After the pandemic	13 - 19	2022

In the two previous regression analyses, which respectively determined the effect of individual characteristics on the probability and the change in probability of working from home, each respondent was seen as an observation. To determine the impact of individual characteristics on mode choice, not the respondents but the trips are used as observations for this analysis. Because a person can make trips with different vehicles, it was not possible to use the respondents as observations. Furthermore, the dependent variable of the previous two analyses was in both cases an interval variable, and therefore a censored regression was used. In this case, the dependent variable is mode choice, which is a categorical variable and each of the observations has one of the options, which are the modes car, bicycle, walking, public transport and teleworking. Therefore, multinomial regression analyses have been performed.

In a multinomial regression analysis, the relationship between the independent and one of the choice options of the dependent variable is always in perspective to the reference choice option. Working from home is selected as the reference category since this allows for a quick comparison fo teleworking with all the other modes of transportation. Because the relationship between the independent variables and each mode of transportation is estimated, regression results for each of the transportation modes with respect to working from home will be returned. Since there are four modes of transportation, besides working from home, four regression tables will be presented per multinomial regression analysis. This chapter will thus contain four different multinomial regression analyses, which all resulted in four regression tables, which amounts to a total of 16 different regression tables. All 16 regression tables are stored in Appendix III. Since there is a high number of independent variables for which the influence of choosing each of the modes of transportation in respective to teleworking is determined, only the most interesting results will be discussed in this chapter.

This chapter is divided into four paragraphs each representing one of the four multinomial regression analyses. These paragraphs discuss the results of the multinomial regression analysis of the selected periods; before the pandemic, in the first weeks of the pandemic, during the whole pandemic and after the pandemic.

5.2.3.1. Before the pandemic

The first multinomial regression analysis concerns the weeks before the pandemic reached the Netherlands. In these weeks, measures regarding working from home had not yet been taken and many people had no experience with teleworking. The regression analysis of these weeks can therefore be used to see which people were already working from home and what characteristics had an influence on mode choice in the normal situation. The results of the other weeks can then be compared to these results to indicate changes. The results of this multinomial regression analysis can be found in

Table 19 in Appendix III.

The results show that in the period before COVID, travel time had a strong negative impact on choosing bicycle as a mode of transportation over teleworking, while the travel time increases the chance of making a trip by public transport. Moreover, construction and office workers had an increased chance to commute by any transportation mode, while people working in ICT or health care were more often working from home. Before COVID, higher educated people commuted more often than lower educated people. Car and bicycle use was more popular amongst people in higher income classes before the pandemic.

Before the pandemic, commuting modes car and public transportation were more often chosen above teleworking by people living in urban areas than people in less densely populated areas. Many people did not have (much) experience with working from home, and therefore car and public transport use could be a solution for those living in non-urban areas to reach their job location.

People owning a car are more likely to use the car for commuting than teleworking, while cycling and public transport are less preferred among these people. Since commuting by car requires in most cases the ownership of a car, it makes sense that these people are more likely to commute by car. Cycling and public transport are alternatives to the car and a negative correlation is therefore also a logical result.

Although the results of productivity and pleasure were gathered during the survey at the beginning of the pandemic, these variables have also an influence on the mode choice before the pandemic started. Persons that indicate experiencing more pleasure while teleworking were often found working from home before the pandemic more than people that indicated experiencing a lower pleasure. In contrast, increased productivity while working from home increases the chance that a person was commuting by any of the four modes of transportation rather than working from home.

This regression analysis has thus resulted in interesting and often explainable results however some of the coefficients are not logical and cannot easily be explained. It is therefore important to once again mention the way that working from home is determined and that it can result in somewhat strange results. For all other weeks, the number of people working from home was determined based on the working days in comparison to the working days in the reference week. However, since the period before covid included the reference week, whether people working from home is calculated differently. Instead of the reference week, the weeks before the pandemic are compared to the mean of all other weeks. People who increased or started working during or after the pandemic are then assumed to be working from home before the pandemic. It is however more likely that people that already worked from home before covid, continued to work from home and are therefore not visible in the NVP data set. The results of regression analysis before COVID are all in reference to working from home, which can thus result in wrong results. Moreover, for the period before the pandemic, just two out of the 20 weeks were selected. A higher number of weeks would increase the validity of the results.

5.2.3.2. During the first weeks of the pandemic

As observed earlier in this chapter (Figure 5 in chapter 5.1), there was a peak in people working from home in the first weeks of the pandemic. In these weeks the Netherlands got just acquainted with the COVID-19 virus and therefore, there was also an urgent advice to work from home, in which the government emphasized the importance to stay at home. A regression analysis of the mode choice during this period gives insight into which people could not work from home during these weeks. Similarly, in the previous analysis, the regression for the first weeks of the pandemic only includes two weeks. Although this time span is shorter than for the next two regression analysis, this analysis will give interesting results on which people were working from home at the start of the pandemic, when most strict COVID-19 measures were applied. The regression analysis results are shown in Table 20 in Appendix III.

According to the travel time coefficient for each of the transportation modes, an increase in travel time decreases the probability that a person walks or cycles to work rather than working from home. On the other hand, an increase in travel time causes an increase in the chance that a person would commute by car or public transport. Although it might be expected that teleworking will be more favourable for longer distances, car and public transport are modes that can be used ideally for longer distances.

When looking at the coefficients for job and function, both industry and healthcare have a positive correlation with both car and bicycle use with respect to teleworking. During these first weeks of COVID-19, many people were advised or forced to work from home. However, people working in healthcare could not work from home and even had to work more as a result of the high infection rate. Also, factory workers could not work from home. Although some factories were closed, factory workers could often still go to work. Therefore, commuting by car and bicycle is positively correlated with these jobs. On the other hand, office workers are less likely to commute by car than people working in another function. Jobs at an office can often more easily be performed from home than other jobs. It makes therefore sense that office workers more tend to choose to telework over commuting by car. However, office workers are more likely to choose public transport over teleworking than employees of other jobs. In most cases, offices are well accessible by public transport and therefore public transport is a more preferred mode amongst those who work at an office. Working in ICT increases the chance of teleworking above all modes of transportation. Like office jobs, jobs in ICT can often be done from distance. These results are in line with the findings of De Haas, Faber, & Hamersma (2020) and Belzunegui-Eraso & Erro-Garcés (2020) that were presented in the theoretical framework.

Higher educated persons tend to prefer cycling and walking over teleworking but teleworking over car and public transport use. Studies by Hjorthol (2006), Astroza, et al. (2020) and De Haas, Faber, & Hamersma (2020) concluded that higher educated persons were more likely to work from home. Although the results that higher educated people are more likely to choose teleworking over car and public transport use are in line with these findings, they prefer cycling and walking over teleworking.

People with higher incomes than lower than modal are expected to have an increasing effect on picking the car as mode of transportation over teleworking. Cycling, walking and public transport use have a decreasing effect with respect to working from home. Car use is often an expensive way of travelling and therefore it is not surprising that higher income classes prefer to go by car. Van der Drift, Wismans,

& Olde Kalter found (2021) a positive relationship between income and teleworking, which is partly reflected in the found results.

When looking at urban density especially walking, and cycling is preferred by people living in more densely populated areas. In highly densely populated areas, the travel times to a destination (in this case work) are often shorter and because cycling and walking are often used for short-distance trips, it makes sense that people in densely populated areas are more likely to walk or bike than in less densely populated areas.

While the coefficient for driver's license shows unexpected results, the coefficients for car ownership are in line with the expectations. Car ownership positively affects choosing car as mode of transportation over teleworking, whilst the correlations between car ownership and all other modes are negative. It can thus be concluded that owning a car improves the probability of choosing a car over teleworking, but decreases the chance of cycling, walking, or going by public transport over working from home. Cycling, walking and especially public transport are often used as alternative transportation modes to the car and therefore these results are not surprising. Moreover, not everyone that owns a driver's license also owns a car, which puts the unexpected coefficient for driver's license in perspective.

Pleasure working from home shows very mixed results for all modes of transportation. Since these results are based on the weeks at the beginning of the pandemic, many people and thus probably also many of the respondents were forced to work from home. Therefore, it comes as no surprise that people who experience different levels of pleasure are working from home.

Productivity shows especially a negative correlation between higher productivity and choosing one of the modes of transportation (except for walking). This entails that higher productivity increases the chance of a person working from home at the beginning of the pandemic.

5.2.3.3. During the whole pandemic

Although the working from home rates dropped after the first weeks of the pandemic, the teleworking advice continued to apply for more than a year. Therefore, a regression analysis has also been performed for all selected weeks during the pandemic combined. Although the government's measures fluctuated during the pandemic, this regression analysis can still be used to determine which people worked from home under the circumstances of a pandemic and which mode of transport they used when they went to work. Table 21 in Appendix III shows the regression results of the multinomial regression analysis for all weeks during the pandemic.

Car is when all other variables are assumed to be zero or reference category the only mode which has a higher predicted probability than working from home. In contrast to the previous analysis on the first weeks of the pandemic, on average more people went working at their workplace. This could also be seen in Figure 6.

The coefficient of the variable travel time shows with teleworking as a reference, a positive correlation with choosing car as commuting mode. On the other hand, travel time has a negative impact on making commuting trips by bicycle, walking or public transport, and thus a higher travel time improves the estimated probability that a person will work from home.

Similarly, to the previous analysis, people working in the industry or healthcare (also in construction for car use) are more likely to commute by car or bicycle than work from home. On the other hand, people working in ICT and/or in an office function are expected to find themselves working from home more often than commuting by any of the modes.

People that have completed medium or higher education are less likely to commute by car than work from home, however, are more likely to commute by walking or public transport. People in higher income classes have an increased chance of going by car, while the chance that they prefer biking, walking or public transport over working from home is much less significant. The relationship between these variables and mode choice is similar to the results of the previous regression analysis and can therefore be explained in the same way. People that completed higher education often have jobs that can be easier performed on distance, while richer people are more likely to own a car and afford the commuting expenses.

The regression results for the whole pandemic show a negative correlation between age and choosing car, bicycle and walking over teleworking. During the pandemic, older people were thus observed to have a higher possibility to work from home. Only commuting by public transport was preferred more over teleworking amongst older people compared to younger people.

Furthermore, a higher density of living location positively impacts the chance of commuting by any mode of transportation over teleworking during COVID. This means that during this period, people living in a lower densely populated area were more likely to work from home than people living in an urban area. These results were also observed in the regression analysis for the period before the pandemic and during the first weeks of the pandemic. Regardless of the implemented measures, living in a low densely populated area increases the probability of working from home. Jobs are often harder to access from these areas and therefore, teleworking is expected to be more likely to be seen as an alternative to commuting for those who live in a less densely populated area.

The influence of driver's license and car ownership on mode choice is comparable to the results in the previous regression analysis. Again, both improve the probability of commuting by car while predominantly negative correlations can be seen with the other modes of transport. The possession of a driver's license surprisingly also positively affects bicycle use. It should be said that people in possession of a driver's license do not all have the option to travel by car and therefore bicycle might be a solution to those.

The coefficients of the pleasure categories indicate that people who experienced more pleasure working from home were more likely to choose commuting and public transport over teleworking than people who experience less pleasure working from home. On the other hand, cycling and walking were less preferred amongst people experiencing pleasure in working from home.

Productivity showed predominantly negative correlations with any of the commuting modes, and thus people who experienced higher productivity favoured working from home during the pandemic more than people experiencing lower productivity during the pandemic.

Persons who live in a single household are, like the last analysis, expected to rather go to their work than stay at home to perform their job. Accessibility of job location increases bicycle and public transport use while decreasing car use with respect to teleworking. People commuting by bicycle or public transport are often much more dependent on the accessibility of a job location than car drivers.

5.2.3.4. After the pandemic

The last, and perhaps the most interesting, regression analysis is performed for the weeks after the pandemic faded (weeks 13-19 in 2022) and after the government announced the withdrawal of almost all measures that were taken to contain the pandemic. This period will probably give the best representation of teleworking and the modal split in the Netherlands in post-COVID times. The regression model created for this period will therefore be used as input for the model analysis in the next chapter (Model results). Firstly, the relationship between all variables and mode choice is determined after which variables will be selected based on whether they increase the goodness of fit of the regression model. Moreover, some variables will also be excluded from the final model because no information on those variables is available in the OmniTrans model of Almere. The regression results including all variables can be found in Table 22 in Appendix III.

When looking at the results it seems that car and cycling are more preferred options than teleworking when all variables are assumed to be zero or the reference category. The intercepts of walking and public transportation are highly negative which means that the probability of choosing one of these two modes of transportation is fairly low when assuming all variables on the reference level. Although cycling is more preferable in the situation of reference categories, it has a strong negative correlation with travel time. The increase in travel time (measured for car use) decreases the chance of taking the bike over working from home. This means thus that the bike is more likely to be used for shorter trips, which is also the case for walking. On the other hand, an increase in travel time by car increases the chance of choosing car or public transport over teleworking.

For the job sector and function categories, similar correlations to the previous regression analysis can be derived. While industry and healthcare positively affect car and bicycle use for commuting, ICT and office workers decrease the chance of taking the car for commuting purposes. It is however striking that working in construction decreases the chance of going to work with any of the modes and are more likely to be found working from home. This result is surprising since for many of the tasks of a construction employee they have to be present at their workplace. Moreover, people in management, research or education functions have an increased chance to travel to work by any mode, decreasing the chance to work from home. Although jobs in ICT or at an office are easier to be done from home, management, research and education jobs can often also be performed from home partially. These results are therefore somewhat surprising and thus indicate that the behaviour of the panel members of the NVP also deviates sometimes from the expectations.

A perceived education improves the choice to walk or go by public transport to work over teleworking, while it causes a reduction in the probability to commute by car or bicycle. People with higher perceived education are thus more likely to telework than to use the car or bicycle to commute to their work location. Higher education is more often required for white collar jobs than for blue collar jobs. In chapter 5.1.3, it was concluded that white collar workers more often worked from home than blue collar workers and therefore it comes as no surprise that people with higher received education are more likely to work from home than commute by car or bike. On the other hand, higher education has a positive correlation with the use of public transport. Although higher educated persons rather work at home than take the car or bicycle, they travel in perspective much by public transport. This is in line with.

The coefficients of the income level are a little different in comparison to the previous regression analyses. Whereas the results of these analyses depicted positive correlations between a higher income level and car use for commuting, the analysis for the weeks after COVID shows something else. According to the results, people that perceived higher education are less likely to choose car over teleworking than lower educated persons. The difference with the other results is remarkable but can be explained. During the lockdown, people were forced to work at home and some businesses were even forced to close. As result, many employees did not travel to their work. During the weeks after the pandemic, people could go to their work again and working from home became more of a free choice. Jobs that make more money are often jobs that can be easier done from home and a positive relationship between higher income and working from home in post-COVID times makes sense.

The independent variable age returns negative coefficients for each of the modes of transport, meaning that an increase in age positively impacts the probability that a person will telework. While a negative correlation between age and working from home was observed before the pandemic, the regressions during the pandemic already yielded more positive correlations. These results show that after the pandemic a higher age increases the chance of teleworking over all commuting modes. Therefore, it can be concluded that a turnaround has been observed in terms of age and working from home. During the pandemic, people of all ages were forced or advised to work from home and according to these results, it seems that older people are more likely to keep teleworking than younger people, who were working from home more before the pandemic started.

Males are more likely to travel to work by car, bicycle, or public transport than females, while females are more often found to be working from home. Again, living in areas with a higher density increases the chance of commuting by any mode of transportation. In the previous paragraph, it was already concluded that living in a lower densely populated area improves the probability of working from home, possibly due to a longer distance to and the lower accessibility of the job location.

The size of the household shows some surprising results. While a bigger household increases the chance to walk or go by public transport in respective to working from home, it decreases the probability that a person commutes by car or bicycle. Both driver's license and car ownership show a positive correlation with commuting by car, while having a negative correlation with the other modes of transportation.

A pleasure to work from home increases car and public transport use, while decreasing cycling and walking to work. Productivity to work from home has a negative effect on commuting by car or bicycle, whilst positively affecting the choice of commuting through walking or going by public transport over teleworking.

Single persons are more likely to go to their workplace, but not by bicycle. The tendency of people in single households to commute to work was also visible in the regression results of the other periods. These people might be more likely to work at their workplace to get social interaction. Accessibility of work location does improve taking public transport or walking to work but commuting by car or bicycle decreases with respect to working from home.

5.2.3.4.1. Variable selection

In conclusion, the regression analysis resulted in a regression model and the impact of independent variables on the dependent variable is discussed above. Although all independent variables can have an impact on the mode choice for commuting, there might independent variables that decrease the model’s goodness of fit. By calculating the goodness of fit of the multinomial regression model, it can be determined how well the model fits the observations. Independent variables that decrease the goodness of fit of the model should be removed from the model. The selection of variables is done through the backward selection method in R Studio and resulted in only the exclusion of household size. Besides household size, every independent variable improves the goodness of fit of the model.

5.2.3.4.2. Standardized coefficients

Earlier in this chapter, the regression results have been analysed and conclusions on the impact of the independent variables on the dependent variable were made. However, the impacts of the different independent variables cannot be compared yet because of the difference in scale. Several variables are binary, meaning that the coefficient is the impact of choosing an option, while other variables are continuous, for which the coefficient shows the effect of changing the independent variable by one. Normally, the binary variables have therefore a relatively higher coefficient than binary or categorical variables.

A standardized regression can be performed, in which the estimated coefficients are standardized, to make comparisons between the independent variables. The input variables for the regression analysis are standardized and the regression analysis is performed again. The results of the standardized regression analysis can be found in Figure 20 in Appendix IV.

By looking at the standardized coefficients, it can be seen that several independent variables have a relatively high impact on the choice of public transport over working from home. It can be seen that public transport has an intercept of almost minus ten, meaning that it is unlikely that public transport is chosen. Walking has also a relatively high negative intercept, while walking is also not preferred by people with lower received education. Furthermore, negative standardized coefficients are observed for all modes for the variables age and ICT, meaning that these positively impact teleworking.

5.2.3.5. Final regression model

Although almost all independent variables improved the goodness of fit of the regression model and were selected through variable selection, not every variable is available in the model of Almere. Moreover, the model of Almere does not include walking as a mode of transportation. Therefore, walking is removed as a category of the dependent variable and independent variables that are not available in the model of Almere are excluded before the regression analysis is performed again. The results of the new multinomial regression model can be found in Table 8.

The results of the new multinomial regression analysis largely match the results of the regression analysis for the full set of variables. When all variables are set to the reference category, both car and bicycle have a higher chance of being chosen as transport mode over teleworking. Public transport is also in this analysis not very favourable and has a strong negative intercept. Increases in travel time cause a decrease in the probability of a person choosing either bicycle or public transport over teleworking.

Again, industry and healthcare have a positive influence on the choice of bicycle and car, while office and education show a negative correlation with the modes car and bicycle. People working in industry or healthcare often do not have the possibility to work from home and are thus indeed more likely to commute by car or bicycle. Office workers of teaching staff have more possibilities to do their work from a distance, thus these results make sense. Surprisingly, all selected jobs have a negative correlation with commuting by public transport.

Higher perceived education increases the chance that a person is going to work from home instead of commuting by bike or car, while higher educated people prefer public transport over teleworking more than lower educated people. Higher education often entitles a person to jobs in which teleworking is easier. Moreover, public transport is a transportation mode which is often used by higher educated people. Similar results were also found in studies by Hjorthol (2006), Astroza, et al., (2020) and De Haas, Faber, & Hamersma (2020) and are presented in the theoretical framework.

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Table 8 - Final regression models for the modes car, bicycle and public transport (ref = teleworking)

	Variable	β	Std. Error	P-value
	intercept	0.858	0.308	0.005 **
	travel time	0.059	0.091	0.519
Sector	Industry (ref = no)	0.351	0.071	0.000 ***
Sector	Healthcare (ref = no)	0.205	0.066	0.002 **
Function	Office (ref = no)	-0.727	0.049	0.000 ***
Function	Education (ref = no)	-0.760	0.121	0.000 ***
	higher education (ref = lower education)	-1.364	0.118	0.000 ***
	medium education (ref = lower education)	-0.580	0.116	0.000 ***
	age	-0.021	0.003	0.000 ***
	Gender (ref = female)	0.378	0.049	0.000 ***
	high density (ref = low density)	0.119	0.058	0.040 *
	medium density (ref = low density)	0.524	0.074	0.000 ***
	household size	-0.041	0.028	0.143
	driver's license (ref = no)	1.277	0.216	0.000 ***
	car ownership (ref = no)	0.330	0.114	0.004 **
household	Adult (ref = single	-0.410	0.074	0.000 ***
household	with children (ref = single)	-0.124	0.104	0.233
	accessibility	-0.049	0.020	0.015 *

Car

	Variable	β	Std. Error	P-value
	intercept	0.997	0.324	0.002 **
	travel time	-2.355	0.181	0.000 ***
Sector	Industry (ref = no)	0.528	0.090	0.000 ***
Sector	Healthcare (ref = no)	0.362	0.080	0.000 ***
Function	Office (ref = no)	-0.327	0.062	0.000 ***
Function	Education (ref = no)	-0.694	0.173	0.000 ***
	higher education (ref = lower education)	-0.738	0.168	0.000 ***
	medium education (ref = lower education)	-0.002	0.165	0.988
	age	-0.013	0.003	0.000 ***
	Gender (ref = female)	-0.030	0.062	0.625
	high density (ref = low density)	0.492	0.077	0.000 ***
	medium density (ref = low density)	0.257	0.103	0.012 *
	household size	0.020	0.039	0.617
	driver's license (ref = no)	-0.278	0.157	0.075 .
	car ownership (ref = no)	-0.626	0.113	0.000 ***
household	Adult (ref = single	-0.161	0.096	0.094 .
household	with children (ref = single)	-0.192	0.139	0.167
	accessibility	0.03	0.026	0.203

Bicycle

	Variable	β	Std. Error	P-value
	intercept	-19.453	1.417	0.000 ***
	travel time	-2.110	0.848	0.013 *
Sector	Industry (ref = no)	-9.602	0.000	0.000 ***
Sector	Healthcare (ref = no)	-1.404	0.824	0.089 .
Function	Office (ref = no)	-1.475	0.364	0.000 ***
Function	Education (ref = no)	-8.460	0.000	0.000 ***
	higher education (ref = lower education)	5.930	0.735	0.000 ***
	medium education (ref = lower education)	6.581	0.724	0.000 ***
	age	-0.040	0.015	0.009 **
	Gender (ref = female)	2.494	0.566	0.000 ***
	high density (ref = low density)	2.277	1.084	0.036 *
	medium density (ref = low density)	0.448	1.301	0.730
	household size	0.508	0.231	0.028 *
	driver's license (ref = no)	-2.253	0.596	0.000 ***
	car ownership (ref = no)	-0.377	0.477	0.430
household	Adult (ref = single	-0.373	0.504	0.460
household	with children (ref = single)	-2.307	0.887	0.009 **
	accessibility	1.581	0.273	0.000 ***

Public Transport

Age has, according to the results of this regression analysis, a negative correlation with each of the modes, meaning that older persons are more likely to work from home than younger persons. Furthermore, it can be derived that males are more likely to choose car over teleworking, while females are more likely to commute by bicycle or public transport. A higher density promotes commuting by any of the modes of transportation and therefore people in less densely populated areas are more likely to be found working from home. Jobs are often harder to access for people living in less densely populated areas and it makes, therefore, sense that these people are sooner to be found working from home. Similar to the full regression model, car and driver's license ownership improve the probability that a person will commute by car over teleworking, while it decreases the chance of commuting with the other modes of transportation. Both adult households and households with children are less likely to commute by any mode of transportation than single households. Lastly, the accessibility of a job location decreases the chance that a person takes the car slightly, while bicycle and public transportation are more preferred when the job location is accessible.

Again variable selection has been applied through backward elimination (explained in paragraph 5.2.3.4.1), which resulted in no eliminated variables. This final model can be compared with the model that includes all variables by comparing the AIC (Akaike information criterion) of the two models. The AIC estimates the prediction error of the model and can be used to determine the quality of the model in comparison to another model. The lower the AIC, the higher the quality of the model is. The AIC of the final model is 20,897, while the the AIC of the full model is 12,572, which means that the full model is of an higher quality. However, the full model includes variables that are not available in the model of Almere and therefore, this final model should be used.

6. Model results

In the previous chapter, a multinomial regression model is created which will be used as input in the OmniTRANS model of Almere to predict the effects of teleworking on commuting patterns. This chapter will start with a comparison between the results of a simulated population and the results calculated and included in the model. The results of teleworking on commuting patterns for car, bicycle and public transport are respectively discussed in a paragraph each. These effects are assessed through three different criteria, which are the modal split, the intensity on the network, congestion and the travel times between Almere and its surrounding cities.

6.1. Simulation of the population

As explained in the method section, the mode choice between each origin and destination zone is recalculated using the regression models presented in page 5.2.3.5. Each regression model can calculate the probability that a person takes one of the modes of transportation for commuting or stays at home to telework. To calculate these probabilities, the model requires characteristics of people in the origin zone, jobs in the destination zone and the trip between these zones. The characteristics present in the model of Almere are discussed in paragraph 4.5.2.1. Before discussing the results of teleworking on commuting patterns, generated by the model of Almere, the available data in the model is compared to the NVP data used to obtain the regression model. The observations in the NVP data are used as a sample to determine the regression model that is used in the model of Almere to estimate effects on the traffic intensities on the network of Almere. The participants of the NVP data live scattered throughout the Netherlands, and can therefore differentiate from the population of Almere. To make safe conclusions on the results generated by the model of Almere, the NVP data should be representative for the population of Almere. A comparison between the characteristics of the persons making the trips made in NVP data (which is used as input for the regression analysis) and the characteristics available one zone level in the model of Almere is presented in Table 9. Significant differences between can be observed in the comparison. When looking at the sector variable, the NVP data deviates from much from the population of Almere. However, the percentages of the NVP data are based on the sector a respondent works in, while the percentages of model stand for the number of jobs in Almere. Since many inhabitants of Almere have a job in another city, no conclusions can be made on this comparison. However, differences are also visible for other characteristics. Among the panel members of the NVP, higher educations levels are more common than in the population of Almere, while inhabitants of Almere live more often in single households and higher densely populated areas than the NVP panel members. Based on this comparison, it can be concluded that NVP data is not very representative of the Almere citizens. Using data on trips solely made by the citizens of Almere would result in a more representative sample, however, the NVP contained not enough data for this.

Table 9 – Comparison NVP observations with the population of Almere in the model

		NVP data	Model data
Observations		19,177	204,008
Average age		47	43
Gender	Male	54%	50%
	Female	46%	50%
Sector	Industry	11%	28%
	Healthcare	19%	4%
Function	Office	44%	31%
	Education	4%	5%
Education	Low	5%	28%
	Medium	51%	44%
	High	43%	27%
Density	Low	26%	7%
	Medium	15%	31%
	High	59%	62%
Household	Single	22%	46%
	Adult	40%	19%
	With children	39%	35%
Car ownership		64%	44%
Driver's license		61%	88%
Average household size		2.69	2.37

The model Almere does not provide information on these characteristics on the individual level, as is required by the regression model, but on the zone level. Although a simulation of the population could help to predict the characters for each individual, this would take much time and is therefore beyond the scope of this study. Although the simulation of the population is outside the scope of this study, populations are manually simulated for three origin and destination zone pairs within Almere to derive the differences between the results with and without simulation of the population. The origin zones were selected under the condition that the zone had inhabitants, while the destination zones needed to include jobs.

A synthesized population was created for each of the selected origin and destination pairs. The number of people was determined based on the inhabitants of the origin zone and each individual gets randomly assigned a characteristic based on the total characteristics of the zone. Moreover, the person gets also randomly assigned a job based on the characteristics of the destination zone.

Table 10 – Difference between simulation population and model for three OD-pairs

Origin: 15 Destination: 340	*Simulation Population*	*Model Almere*	*Difference*
Car	50.42%	40.69%	9.73%
Bicycle	15.92%	26.12%	10.20%
Public Transport	0.01%	0.00%	0.01%
Working from home	33.65%	33.18%	0.47%
Origin: 446 Destination: 282	*Simulation Population*	*Model Almere*	*Difference*
Car	50.61%	34.84%	15.77%
Bicycle	21.48%	34.07%	12.59%
Public Transport	0.00%	0.00%	0.00%
Working from home	27.91%	31.09%	3.18%
Origin: 422 Destination: 220	*Simulation Population*	*Model Almere*	*Difference*
Car	55.51%	41.20%	14.31%
Bicycle	14.96%	24.29%	9.33%
Public Transport	0.18%	0.00%	0.18%
Working from home	29.35%	34.51%	5.16%

Similar to the regression model, the simulated population was used to calculate the probabilities that a person living in an origin zone, while working in a destination zone would either take any of the modes for commuting or goes teleworking. The probabilities calculated with both the simulated population and with the model for the three origin-destination pairs have been displayed in Table 10. This table includes also the differences between the probabilities for each mode.

The differences between the probabilities calculated with the simulated population and with the model show similar results for the three origin-destination pairs. In each of the cases, the estimated probabilities calculated with the zone averages in the model Almere deviate from the probabilities manually calculated with the simulated population. The difference is especially visible in the probabilities for car use. The calculated probabilities of commuting by car in the model Almere for these OD-pairs are much lower than the probabilities calculated with the simulated probabilities. For the three samples, these differences lie between 9.7% and 15.8%, which is thus a significant difference. The lower probabilities of using a car in the model of Almere are compensated by higher bicycle and working from home probabilities. The bicycle probabilities tend to be around 10% higher when calculating the probabilities with average numbers, while the difference in working from home fluctuates between zero and five per cent.

Although simulating the population for the entire model of Almere is beyond the scope of this study, these manually simulated sample populations can be used for a better interpretation of the results. When analysing the outcomes of the traffic intensities in the model of Almere, it should be considered that the results in the model overestimate bicycle use and to a lesser extent working from home, while underestimating car use.

6.2. Modal split

To determine the impact of teleworking on mobility, the modal split in the model of Almere has been recalculated using the regression model presented in paragraph 5.2.3.5. The modal split was redefined for each origin-destination pair, using the regression model.

Originally, the model of Almere only included the modes car, bicycle and public transport. In this research, teleworking was added as an extra mode of transportation to see the switch between conventional modes and teleworking.

One of the assessment criteria to assess the impact of teleworking on mobility can be found by determining the modal split for trips with all purposes that started or ended in Almere. The modal split has been calculated for the situation before and after the inclusion of teleworking in the model. By analysing the model split before and after implementing teleworking in the model, changes in mode use can be observed. The modal split with and without the inclusion of teleworking is visualised in Figure 11.

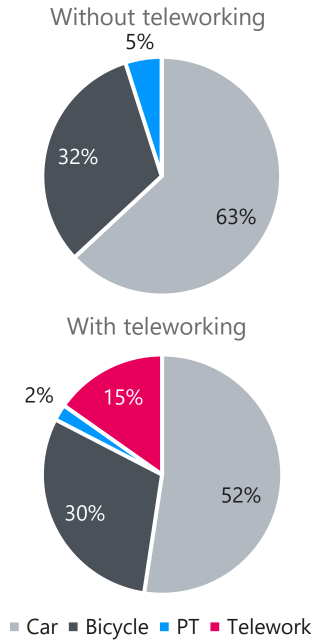

Figure 11 - Modal split in model Almere for trips with all purposes

From the results in the circle diagrams, it can be depicted that it is expected that 15% of all trips are replaced by teleworking, based on the regression model and the characteristics present in the model. A decrease in the modes car, bicycle and public transport can thus be observed. Both with and without the inclusion of teleworking, the mode car accounts for the largest share of trips. However, a decrease from 63% to 52% of the trips is expected. On the other hand, bicycle trips experienced a relatively lower decrease from 32% to 30%.

According to these results, public transport trips are more than halved due to the implementation of teleworking. This observation is not unexpected since in the NVP dataset only 0.6% of the work-related trips was made by public transport (Figure 7). These work-related trips in the NVP dataset were used for the calculation of the regression model which is ultimately used to determine the modal split. Moreover, public transport use saw a significant decrease due to the COVID-19 pandemic, which is also reflected in the NVP dataset.

The addition of teleworking in the model of Almere caused thus a decrease in all modes, while the biggest decreases were observed for car and public transport use. These two modes are more often used for long-distance commuting. In the following paragraphs, the resulting impact of the decreases in trips by car, bicycle and public transport on mobility aspects traffic intensity and travel times are assessed.

6.3. Car patterns

According to the behaviour of the panel members of the NVP, the car is the most frequently used vehicle for commuting (depicted in Figure 7). Due to the pandemic, a substantial part of these panel members switched from commuting by car to working from home (Figure 6), which is also reflected in the implementation of teleworking in the model of Almere. In the modal split of the model, the share of car decreased from 63% to 52% due to the implementation of teleworking. This decrease will have effects on existing commuting patterns, such as traffic intensities, congestion and traffic times. Expected post-COVID traffic intensities have been determined for all trips starting or ending in Almere and can be compared to the traffic intensities present in the model of Almere without the addition of teleworking. Since commuting traffic is especially present in the morning rush hours, differences in traffic intensities are analysed. Figure 12 depicts the differences of car traffic intensities within Almere as well as the out- and ingoing traffic intensities. Moreover, the differences in morning rush hour car intensities are visualised in Figure 13.

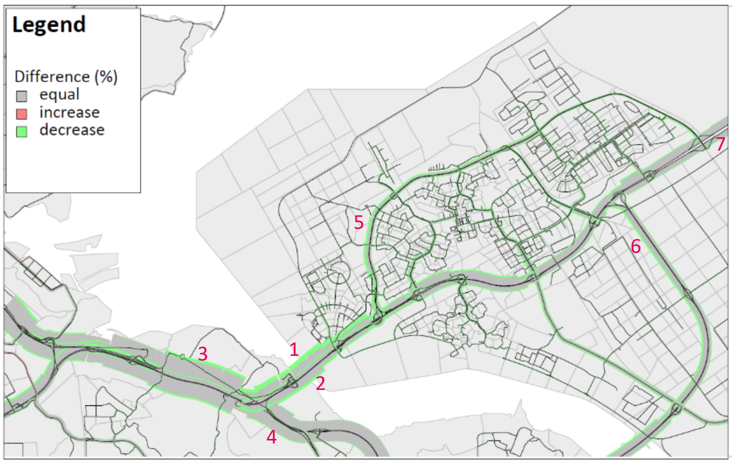

Figure 13 - Visualisation of difference in car intensities during morning rush hour between before and after the implementation of teleworking

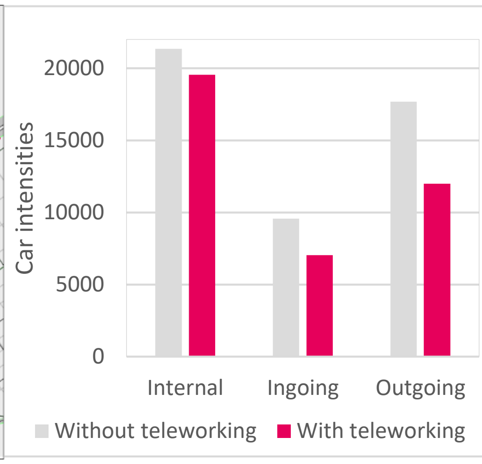

Figure 12 – Morning rush hour car intensities in Almere with and without teleworking

Both the graph in Figure 12 and the visualisation in Figure 13 show decreases in motor vehicle intensities during the morning rush hour. The biggest decrease in car intensities is observed in the trips that start in Almere and have a destination outside Almere. As has been mentioned earlier in this report, Almere often serves as a commuter city for Amsterdam and thus these decreases are in line with the expectations. Furthermore, in- and outgoing trips are usually longer than internal trips. It seems thus that longer trips are more often replaced by commuting than trips of a shorter kind.

Especially on major roads, there is a significant decrease in car traffic during the morning rush hour. In Figure 13, seven points have been selected and numbered, to see where on the network the decreases are located. The (difference) in traffic intensity on these points can be found in Table 11. On all the selected links the traffic intensity decreased between 19% and 42%. The largest absolute decrease is estimated on the bridge between Almere and Amsterdam in the direction of Amsterdam (point 1). The traffic flow for commuting between Almere and Amsterdam is normally fairly high because many people are living in Almere while working in Amsterdam. When a significant part of these people decides to work from home, it will thus lead to a decrease in traffic intensities, especially in the morning rush hour, when the largest part of the trips has a commuting purpose.

Table 11 - Traffic intensities in the morning rush hour on the selected points in the network

	Traffic intensity (x 1,000)			
Nr.	**Before**	**After**	**Difference**	**%**
1	11.3	7.6	-3.8	-33%
2	7.7	5.4	-2.3	-30%
3	17.4	14.0	-3.3	-19%
4	1.1	0.8	-0.2	-23%
5	2.9	1.7	-1.2	-42%
6	2.4	1.4	-1.0	-21%
7	4.5	3.4	-1.1	-30%

Furthermore, the highest percentage decrease among the selected point was found on link number 5, which is provincial road N702. This road goes in the direction of the highway A6 which can be used to access neighbouring cities such as Amsterdam and Utrecht. The decrease in traffic intensity on the N702 is thus also in line with the expectation that especially people commuting to other cities are more likely to work from home.

To see how these decreases impact the citizens of Almere and their commuting behaviour, the congestion on the network and the travel times between Almere and its surrounding cities are assessed. Although congestion was not calculated in the model of Almere, it can be approached by determining the Intensity-Capacity (IC) ratio. Each of the roads in the network contains a capacity that indicates the number of cars that can be on the road at the same time. The IC ratio compares the capacity of the roads with the intensity (these are visualised in Figure 12). When the intensity on a road is more than 100% of the capacity on that road, it means that the road has not enough capacity for the cars on the road, meaning that there is congestion on that link. In cases of an IC ratio close to 100, the traffic intensity is high compared to the capacity of the road and thus can thus result in congestion or slow-moving traffic. The IC ratios on the network in the model of Almere before and after the inclusion of teleworking are displayed in Figure 14. It is thus expected that teleworking has a congestion decreasing impact.

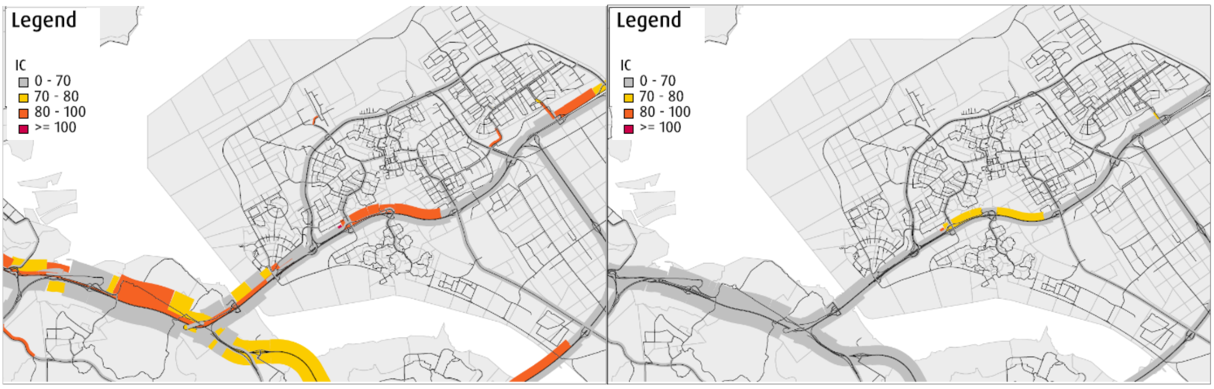

Figure 14 - Visualisation of car Intensity-Capacity (IC) ratio; left without and right with the implementation of teleworking

By comparing the IC ratios on the network before and after the implementation of teleworking in the model, significant differences can be observed. In the situation where teleworking is not implemented in the model, IC ratios between 70 and 100 can be seen on several links, mainly on the highways. After the implementation of teleworking, the IC ratios seem to be decreased and high IC ratios hardly occur. An increase in teleworking among the citizens of Almere has thus a congestion decreasing effect.

To determine whether the reduction in congestion impacts the inhabitants of Almere, the travel times between Almere and its surrounding cities are calculated. The travel times from Almere to the cities of Amsterdam, Utrecht, Zwolle and Harderwijk are presented in Table 12. Minimal differences in travel time can be observed as a result of the implementation of teleworking. The biggest decrease in travel times is expected to be between Almere and Amsterdam and is just over a minute. Between Almere and Zwolle and Harderwijk, the reduction is only 15 to 20 seconds. It seems thus that, although it has a congestion-reducing effect, teleworking impacts the travel times of the inhabitants of Almere only a little. However, when taking a quick look at the travel times between Almere and these cities on Google Maps, much higher travel times can be seen during the morning rush hour. According to Google, the travel times between Almere and Amsterdam fluctuate between 28 minutes and an hour during the morning rush hour. The

Table 12 - Travel times from Almere before and after the inclusion of teleworking

	Before	After
Amsterdam	25'35"	24'34"
Utrecht	34'34"	33'49"
Zwolle	55'59"	55'44"
Harderwijk	36'37"	36'18"

travel times calculated by the model of Almere are more comparable to the travel times outside rush hour. The model of Almere is a static model, and therefore underestimates the loss in travel times. Therefore, teleworking could have a stronger reducing impact on travel times than the results displayed in Table 12 show.

6.4. Bicycle patterns

Unlike car use, bicycle use amongst the NVP panel members remained pretty constant during the pandemic (see Figure 6). After the measures were lifted, a similar number of commuting trips per person by bicycle was observed as in the weeks before the pandemic. However, bicycle use can differ throughout the year, depending on the weather and temperature (CBS, 2020). The post-COVID data was gathered in the spring while the pre-COVID data was collected during the winter, which might thus favour the bicycle use in the post-COVID data.

The results of bicycle use within the model of Almere showed initially remarkable results. Especially on roads used for long distance trips, significant increases in bicycle use was observed. The probability that the bicycle is used for a trip, is like the other modes, based on the regression model that was determined in paragraph 5.2.3.5. Although the regression model incorporates travel time, which was estimated to have a decreasing influence on bicycle use, there is still a probability that the bicycle is used for longer distances. This is the result of an incorrect assumption of linearity between travel time and bicycle use for commuting. By analysing all work-related trips in the NVP data it was found that over 99% of the trips made by bicycle had a travel time below an hour, while a very large share of the trips was also below half an hour. The results generated with the model for bicycle use for long-distance trips are therefore assumed to be wrong. Therefore, bicycle use was excluded from the trips going in or out of Almere and only the bicycle trips within Almere are analysed. Whereas a significant decrease in car intensities was observed, bicycle intensities remained fairly constant. Before the implementation of teleworking, a the model of Almere estimated 139,240 bicycle trips in the morning rush hour within Almere. This total decreased slightly to 136,841 trips with the inclusion of teleworking. Since bicycle traffic is usually not as centered on main roads as car traffic and analysing intensities throughout the entire city can be quite messy, it is chosen to focus especially on the bicycle intensities in the centre of Almere. The centre of Almere is an attractive destination for cyclists since it contains several job locations as well as the train station. Differences in morning rush hour bicycle intensities before and after the pandemic for the centre of Almere are visualised in Figure 16.

Figure 16 - Visualisation of difference in bicycle intensities in Almere centre during the morning rush hour before and after the implementation of teleworking

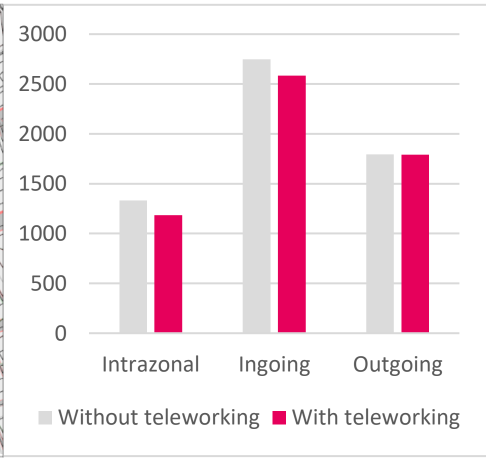

Figure 15 - Morning rush hour bicycle intensities in Almere centre with and without teleworking

As can be derived from Figure 15, the bicycle intensities in the centre of Almere slightly decreases with an increase in teleworking. The decreases are mainly visible in the ingoing and internal traffic. Due to its job locations and train station, the centre of Almere is an attractive destination for commuters. The decreases in ingoing and internal traffic in the morning rush hour are therefore also in line with the expectation that teleworking reduces commuting traffic. The visualisation of the bicycle intensities in Figure 16 shows both decreases and increases on the network. On long continuous streets, mainly increases can be seen, while smaller roads show more often a decrease. This is also due the error that the model overestimates bicycle use on long distance trips. Furthermore, several links show a decrease in trips towards the train station (which is located left next to point 1) and an increase in trips going opposite direction. A decrease of trips toward the station is a direct result of the increase in teleworking.

Two links in the network have been selected to analyse the traffic intensity before and after the inclusion of teleworking. The intensity on these links is displayed in Table 13. Point one is located on a long continuous road which runs parallel to the train track. On this link an increase of 22% was observed. In contrast, the link indicated with point two experienced a decrease of bicycle traffic in the direction of the train station.

Table 13 - Bicycle intensities in the morning rush hour on the selected points in the network

	Traffic intensity			
Nr.	**Before**	**After**	**Difference**	**%**
1	339	413	74	+22%
2	323	301	-22	-6.8%

6.5. Public Transport patterns

Public transport use among the members of the NVP panel was already quite low before the pandemic (Figure 6) but during and after the pandemic it was even less used as a mode of transport for commuting. This significant decrease in public transport use is also reflected in the traffic intensities in the model of Almere. The public transport intensities for Almere before and after the implementation of teleworking are presented in Figure 18, while Figure 17 displays the visualisation of the difference between the original public transport intensities and the estimated public transport intensities after the pandemic.

Figure 17 - Visualisation of difference in public transport intensities during the morning rush hour between before and after the pandemic

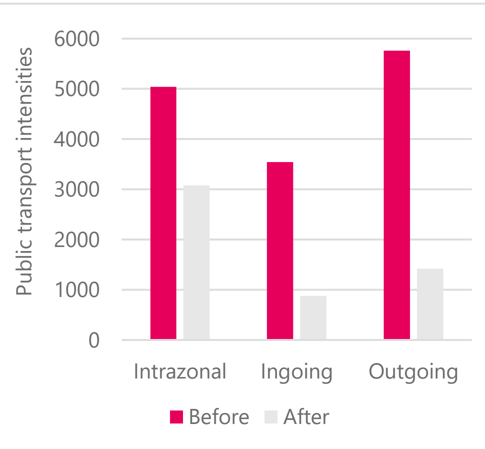

Figure 18 - Morning rush hour public transport intensities in Almere with and without teleworking

Figure 18 shows significant decreases in public transport intensities during the morning rush hour in Almere. The highest decreases can be seen in in- and outgoing public transport trips. Before the pandemic, public transport was often used as commuting mode to reach a job destination in another city. These trips are likely to be replaced by teleworking. The significant decreases in public transport intensities can also be derived from Figure 17, which is not surprising considering the low amount of public transport use amongst the NVP panel members in the post-COVID situation.

Two links on the network have been indicated with a number in Figure 17 and for both links the traffic intensity in two directions is presented in Table 14. The link highlighted with number one is a train link between the station of Almere and the stations of Amsterdam and Utrecht. Direction 1 of this link indicates movement away from Almere, while the train intensity towards Almere station is stored under direction 2. There is a significant difference in traffic going towards and going away from Almere. The intensity of train traffic is more than double as high as the train intensity in opposite direction. This proves once again that inhabitants of Almere often work outside Almere. In both directions a decrease in intensity between 40 and 50% is observed. It should be noted that this link also contains trips neither starting nor ending in Almere. These trips are not recalculated because this study focused on the commuting patterns of the inhabitants of Almere.

Table 14 - Morning rush hour PT intensities in Almere centre with and without teleworking

		Traffic intensity			
Nr.		Before	After	Difference	%
1	1	7,505	4,410	-3,095	-41%
	2	3,660	1,934	-1,726	-47%
2	1	1,030	374	-656	-64%
	2	837	427	-410	-49%

This is also the reason that the declines on the link indicated with number two are higher. Link two is a bus link close to the station of Almere of which (almost) all trips start or end in Almere. The effect of teleworking is therefore more measurable on this link. Towards the station (direction one), a decrease of 64% is observed. The bus line towards the train station can be a part of a commuting trip to be continued by train, while it is also possible that people take the bus to travel to their work location in the city centre, close to the train station. An increase in teleworking is expected to decrease commuting trips, thus these observed decreases are in line with the expectations. On the other hand, the observed decreases are very high, also when compared to bicycle and car decreases. The use of public transport saw an enormous decline during the pandemic. At the time the data, used for the analysis 'after the pandemic', was gathered the use public transport had not returned to pre-COVID levels. At time of the writing of this thesis, a half year after the collection of the data, public transport use has increased and is almost returned at pre-COVID levels. Moreover, the use of public transport was relatively low among the NVP panel members. These things should be kept in mind when making conclusions on these results.

6.6. Sensitivity analysis

The implementation of teleworking in the model showed thus that teleworking has impacts on traffic intensity, congestion, modal split and to a lesser extent travel times between Almere and other cities. However, these results are based on data gathered just after the advice to work from home was abolished. Many people still worked from home during this period. However, it is likely that people are going more often to their workplace and working less from home as the pandemic will be further in the past. Therefore, a sensitivity analysis has been performed to find out at which rates teleworking still has a significant impact on commuting patterns. To do this, the number of teleworking trips has been reduced multiple times by different amounts, which caused other modes of transportation to increase. For example, the teleworking numbers are reduced by 50%, which means that half of the calculated trips replaced by teleworking during the period after COVID-19, is still dedicated to teleworking. By using different percentages, a minimal teleworking ratio can be found for which it still has the desired impact on the traffic intensities. This ratio is assessed by analysing the congestion in different scenarios. Figure 19 shows the IC-ratio on the network of Almere for scenarios that 50% and 85% of the commuting trips is still replaced by teleworking. When comparing the 50% scenario to the situation before the implementation in Figure 14, decreases in the IC-ratios can be seen on some links. However, the IC-ratio on the road between Almere and Amsterdam is still above the 70% in the morning rush hour, which can cause congestion travel time losses. Therefore, the telework ratio was adjusted to find the minimal percentage of the current teleworkers to remain working from home for which the IC-ratio on the roads between Almere and Amsterdam are reduced to below 70. This resulted in a scenario of 85%, which means that if in 85% of the teleworking cases, the person keeps teleworking in the future, an positive impact on the congestion between Almere and Amsterdam can be observed.

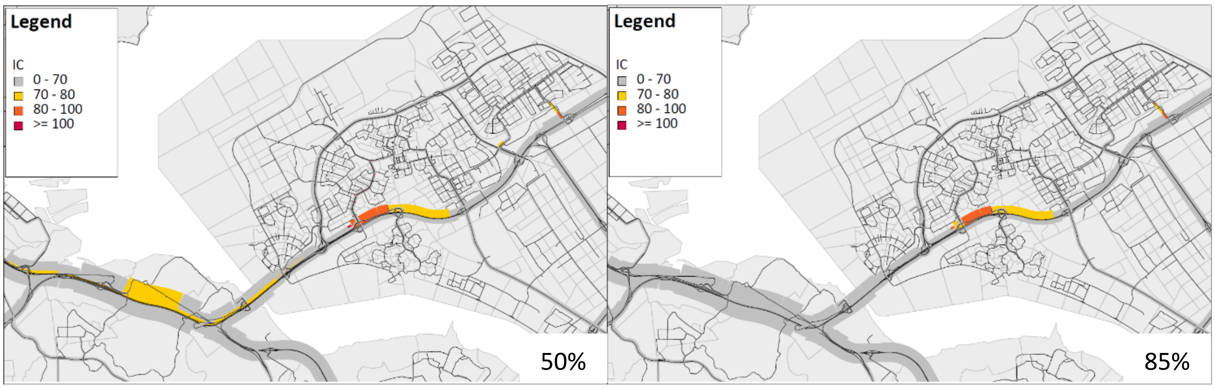

Figure 19 – visualisation of the IC-capacity at the network in Almere for the 50% and 85% telework ratios

Moreover, the traffic intensities on the bridge between Almere and Amsterdam and the travel times between these two cities are analysed in the two scenarios. In the 85% scenario the traffic intensity on the bridge is estimated to be 8.5 thousand in the morning rush hour, which is considerably less than the 11.3 thousand in the scenario without teleworking. In the 50% scenario 9.2 thousand vehicles are expected on the bridge between Almere and Amsterdam. Although the travel time was not expected to decrease much as a result of the implementation of teleworking, it still showed that teleworking can have a travel time reducing effect. Moreover, it is expected that the model underestimates the actual reductions in travel time. In the 50% scenario, a trips between Almere and Amsterdam is estimated to be 25 minutes, which is more than 30 seconds faster than a situation without teleworking. In the case of the 85% scenario, this travel time is 24 minutes and 48 seconds, which is slightly faster than in the 50% scenario. From this sensitivity analysis, it can be concluded that also to a lesser extent, teleworking has an observable impact on traffic intensities and commuting patterns. When half of the decline in commuting traffic due to teleworking remains, this has already impacts on the congestion and travel times, while when the observed teleworking numbers decrease by 15%, almost no congestion is expected between Almere and Amsterdam.

7. Discussion

During this study, the effects of teleworking on commuting patterns have been analysed. Moreover, teleworking behaviour before, during and after the COVID-19 pandemic as well as characteristics affecting teleworking and mode choice are researched. Although interesting results were gathered by the analyses performed during this study, some methods and results need to be discussed. This chapter discusses assumptions made during this research and the limitations of the study.

In the beginning of the research, a conceptual model has been developed in which the topics of this study were discussed. The relationship between these topics was found in the literature and have also been researched in this thesis. Three main relationships could be identified in the conceptual model. The first being the influence of the COVID-19 pandemic and the advice to work from home on teleworking. Similarly to the findings in the literature (De Haas, Faber, & Hamersma, 2020), an increase in teleworking during the COVID-19 pandemic and the accompanying advice to work from home. The results in this research were a little higher, but did not deviate too much to be unrealistic. The findings in the literature did not determine the teleworking rates after the pandemic, which were found in this study. Moreover, Hamersma, Krabbenborg and Faber conducted a survey in which they concluded that 27% of the people working from home during the pandemic expects to remain working from home after the pandemic. In this study the percentage of trips replaced by working from home is a little higher, namely 40%.

During the regression analysis, the effects of characteristics on (the change in) teleworking and mode choice have been identified. In most cases, these effects did match the findings in the literature and the expectations, however also surprising results were found for which no explanations were found.

The second relationship is the relationship between individual characteristics and teleworking. Regression analysis has been performed throughout this research to find this relationship these results can be compared to the findings in the literature.

In the literature mixed conclusions were made on the relationship between age and teleworking during the pandemic. Whereas De Haas, Faber and Hamersma (2020) found a negative relationship, Van der Drift, Wismans and Olde Kalter (2021) concluded the opposite. The results on the impact of age on teleworking during the pandemic that were found in this study were also mixed or not significant. However, the relationship between age and teleworking was found in later stages of and after the pandemic. Older people were also found to be more likely to increase working from home than younger people.

Relationships between higher education and teleworking (Hjorthol, 2006; Astroza, et al., 2020; De Haas, Faber, & Hamersma, 2020) and higher income and teleworking (Van der Drift, Wismans, & Olde Kalter, 2021) were also found in the literature. An positive impact of higher education on teleworking was also found during this study. However, no clear relationship between higher income and working from home was found. The regression analysis between individual characteristics and the probability of teleworking returned even a negative correlation, although it was not significant.

In this research the results showed that office workers and people working in ICT were more likely to work from home, while industry and healthcare workers were found more often working from the workplace. This is in line with the findings in the literature presented in paragraph 3.2.1 (De Haas, Faber, & Hamersma, 2020; Belzunegui-Eraso & Erro-Garcés, 2020).

The last main relationship indicated in the conceptual model is the relationship between teleworking and the effects on modal split, traffic intensity, congestion and travel times. De Haas, Faber and Hamersma (2020) found a reduction in traffic intensity of 55%, while Van der Drift, Wismans (2021) and Olde Kalter concluded a reduction of almost 50%. This research resulted also in a decrease in traffic intensity but not as high as found in the literature. During the morning rush hour, the traffic intensities decreased by 20% to 40% on the main roads. In contrast to the study by De Haas, Faber and Hamersma (2020), the results from this study are post-COVID and thus are logically not the same.

Moreover, a decrease in congestion, emissions and traffic safety were expected results of teleworking found in the literature (Giovanis, 2018). Although this study did not examine the impact of teleworking on emissions and traffic safety, decreases in congestion have been observed due to the implementation of teleworking in the model.

The literature also showed a significant decrease in public transport due to the increase in teleworking, especially among higher educated people (De Haas, Faber, & Hamersma, 2020; Van der Drift, Wismans, & Olde Kalter, 2021). This decrease was also observed during this study and was not only observed during the pandemic but also after the pandemic. Moreover, relationships between higher educated people and teleworking was found during this research, except in the first weeks of the pandemic. This is also in line with the findings that in the beginning of the pandemic public transport use decreased significantly among higher educated people.

7.1. Assumptions and limitations

Throughout this master thesis, several assumptions have been made. These assumptions, as well as other things, make cause limitations to this thesis. In this section, the made assumptions will be listed, and the limitations are going to be discussed.

People had to be active during the selected week for them to be included in the analysis. When a respondent made at least one trip, regardless of the purpose, it was assumed that the person was active during that week. If a panel member is active during a week, it was assumed that this person was working this week as much as they were working during the reference week.

Especially in the data preparation phase of this study, a lot of assumptions had to be made to get the desired dataset. Initially, the data contained individual trips made by the members of the NVP panel, including information on the trip and the person making the trip. The information indicated per trip the purpose of the trip. Unfortunately, the motives of work and business were combined into one motive. Since it was not possible to separate the trips into two motives and business trips are usually much less common, it is assumed that all the trips with the work/business motive are trips to and from work.

The individual work trips, which were present in the dataset, were aggregated into working days to make the dataset clearer and to prevent double counting of split commuting trips. During this aggregation, two assumptions were done. Firstly, if a person made at least one work-related trip during a certain day, it was assumed that this person commuted that day. As a result of this assumption, multiple (more than just home-work and work-home) commuting trips are not included. When aggregating single trips into days, the mode of transport should also be selected, as this can differ between the aggregated trips. In case there is a difference between these trips, it is assumed that the mode which is used to cover the highest distance on work-related trips on the day, is the mode used for commuting for that day. In case there is a tie in covered distance between two or more modes of transportation, the following priority is applied: car - bicycle - walking - public transport.

To reduce the number of categories and increase the difference amongst them categories of some independent variables were merged into more comprehensive categories. However, this also resulted in information loss since a higher number of categories can result in more detailed results. Moreover, due to the nature of the data, namely survey data, there were a lot of missing or unknown values. In some of these cases, records with missing values were excluded, while in other cases a value was assumed for missing or unknown values. For example, driver's license and car ownership are binary variables including the options yes or no, however, in some cases, the answer was unknown or missing. When this was the case, a value of 0.5, which is the mean of the binary options 0 and 1, was assumed.

Another independent variable included in the regression analysis is the travel time for commuting. Since it was hard to make a distinction between commuting and business trips, it was not possible to gather information on travel time from the NVP data. However, the NVP data did contain information on the postal code of residential and work locations. The travel time is therefore assumed to be equal to the time between those postal zones. Since these postal zones were on PC4 level, the travel time depends on where in the PC4 zones the trip starts and ends. Moreover, several respondents did not share their living and/or work location and these were thus not included in the analysis. Another point regarding the travel time that should be addressed is that car travel time is used as a characteristic to determine the probability of choosing each of the modes. Travel times for public transport and bicycle will result in a more realistic correlation respectively with public transport and bicycle use for commuting, however, it is not possible to include travel times for each of the modes, due to correlation.

In the research, data was retrieved from the NVP panel and is used to estimate teleworking and commuting patterns for the inhabitants of Almere. However, a comparison between the NVP sample and the population of Almere showed that the sample taken from the NVP data is not representative of the population of Almere. This could lead to wrong assumptions on travel and telework behaviour of the inhabitants of Almere. As a result, the estimated effects of teleworking on traffic intensities and commuting patterns in the model of Almere might thus differentiate from the actual impact of teleworking in Almere.

This study knows two big limitations, the first of which refers to the choice of the regression model. The data set used to research the relationship between different characteristics and the mode choice included working days. For each working day, it was checked whether a person made a trip by car, bicycle, public transport or walking or that the person was working from home. This choice in combination with the characteristics of the person was then used to determine the effects of characteristics on mode choice. The limitation of this study is that persons could have made multiple trips, which leads, using a multinomial regression, to a bias towards people that made multiple trips. Their characteristics are then more often used to determine the effects on mode choice. A nested or mixed logit model would be better suited for this research, however these required alternative-specific variables. The used variables were all related to the individual making the trip rather than the modes of transportation.

The second limitation regards the assumption of linearity between the independent variables and the dependent variable. The model of Almere does not include characteristic information on an individual level but on the zone level. Therefore, mean values of zones have been used to determine the probability of each mode to be chosen. Many of the independent variables did however not expect a percentage or mean value but rather the choice for one of the categories (binary and categorical variables). By filling in a percentage, linearity between the independent and dependent variable is assumed. A simulation of the population for each of the zones would prevent this assumption but is however beyond the scope of this study. A simulation of the population has been performed for a selected group of origin-destination pairs to determine the differences between results generated by filling in the regression model with mean values and results based on a simulated population. These results showed a significant difference between those. Car use was underestimated by the used method, while it overestimated bicycle use and working from home in comparison to the simulated population.

8. Conclusion

Due to the COVID-19 pandemic, the Dutch government introduced measures to contain the virus, including measures that forced or advised people to work from home. During this master thesis research, different analyses have been performed to see the effects of teleworking on commuting patterns and whether and whether people will remain to work from home, even after the pandemic. In this conclusion, an answer will be given to the research questions that are proposed in chapter 2.3. Moreover, recommendations are given for further research.

8.1. Answering the research questions

The research question of this study reads as follows; *What are the possible effects of teleworking on commuting patterns for residents of Almere?* Before answering the research question, an answer is given to each of the sub-questions.

1. *Which mobility patterns of commuting trips can be extracted using available data collected during the COVID-19 pandemic?*

According to the results of the data analysis, the COVID-19 pandemic caused a change in commuting behaviour. Teleworking numbers multiplied during the first weeks of the pandemic, due to restrictions and the advice to stay at home. In these weeks well over 50% of the working days were performed from home. After the first weeks, the number of people teleworking decreased slightly to around 40% and even after most of the government's restrictions were lifted, people remained working from home. The rise of working from home was of the expense of commuting trips and for all modes of transportation, a decrease was observed. Although all modes of transportation experienced a decline in the number of trips, especially car and public transportation were used much less during and after the pandemic. The mean number of bicycle trips per person after the pandemic is almost equal to pre-COVID, while the car and public transport are nowhere near the pre-COVID number of trips.

When looking at who is working from home and who is still going to their workplace, two groups of people have been distinguished: blue- and white-collar workers. White-collar workers were more often found to be working from home, while their counterparts were more often present at their workplaces to perform their jobs. In all weeks during and after the pandemic, commuting by car was more popular than working from home for people working in blue-collar jobs. On the other hand, white-collar workers preferred working from home over commuting by car in all of the selected weeks. Furthermore, blue-collar workers were more likely to use the bicycle, while public transportation was more popular as a commuting mode among white collar workers.

2. *Which individual characteristics affect the probability of teleworking and what changes in teleworking and mode choice can be observed?*

In the data analysis, several different regression analyses have been performed to determine which characteristics explain the probability that a person works from home, which people changed their working from home behaviour during the pandemic and the mode choice of people during different periods before, during and after the COVID-19 pandemic.

Following the results, several individual characteristics influence the probability that a person goes working from home post-COVID. People working in industry and healthcare have a decreased probability of working from home, while office workers will more likely work from home. Jobs in industry and office require very often employees to be present at the workplace, while people with an office function can more easily perform their jobs from home. Furthermore, people that indicated in the survey that they were working from home because they did not like travelling to work anymore are more often found to be working at home also after he pandemic. Also, productivity seems to affect the probability of working from home. People that indicated experiencing higher productivity while working from home have an increased chance to work from home with respect to people who perceive to be less productive at home. Finally, density also impacts the chance of working from home. The results depict that people living in less densely populated areas are more likely to work from home. From low densely populated areas, it is often harder to access job locations, thus inhabitants of these areas might be working from home more often. An overview of the impacts of the highlights variables can be found in Table 15.

Table 15 – Variables and their impacts on the probability of teleworking

Sector	Industry	-
	Healthcare	-
Function	Office	+
Reason working from home	Not liking commuting	+
Increased productivity working from home		+
Low urban density		+

The change in working from home between the beginning of the pandemic and when the measures were lifted could be best explained by the variables pleasure and age. Persons who experienced more pleasure working from home increased working from home more often than people who experienced less pleasure. It is thus expected that a person will be more likely to increase or keep working from home when they experience pleasure while teleworking. The results showed that age has a positive correlation with the change in working from home. It seems to be that older people are more inclined to keep or increase working from home than people of a younger age. Moreover, variables medium and higher education also showed somewhat significant effects on the change in working from home. People that perceived either medium or higher education are expected to decrease working from home after the pandemic more likely than lower educated persons, while people higher educated people were seen more often working from home during the weeks after the pandemic. Although higher educated people decreased teleworking since the measures were lifted, they still are more likely to work from home than people with lower received education. Table 16 shows an overview of the variables that influence on the change in probability of teleworking.

Table 16 – Variables and their impacts on the change in teleworking probability

Increased pleasure working from home	+
Age	+
Medium education	-
Higher education	-

Lastly, the impacts of characteristics on mode choice during different periods before, during and after the pandemic are analysed. Firstly, the results showed a positive correlation between travel time and car and public transport during most of the periods, while walking and cycling were less preferred over teleworking when the travel time increases. The transportation modes car and public transport are more suited for long-distance commuting, while walking and cycling are better suited for short trips to work. Looking at the expected correlations between jobs and the mode choice, it can be derived that except in the weeks before the pandemic, people working in the industry and healthcare were more likely to commute by car or bicycle. In most cases, these jobs cannot be performed from home and employees, therefore, continued working even during the pandemic. On the other hand, persons working in ICT or in an office function were less likely to commute by car than to be working from home during and after the pandemic. Public transport was a more preferred mode of transport for office workers, except for the period covering the whole pandemic. Over all selected weeks in the pandemic, office workers were more likely to work from home than commute by any of the transportation modes. During this period, the government's advice to work from home was in place. Higher received education increases the probability to work from home over commuting by car in the weeks during and after COVID-19 while walking and commuting by public transport are more preferred by higher educated people than lower educated people. Before and at the beginning of the pandemic, higher educated people were more often observed to be cycling to work than lower educated people however this changed as the pandemic progressed and even faded. Among people with higher incomes, the car is more often used over teleworking than amongst people with lower incomes, while working from home is preferred over all other modes. Although people with a higher salary used the car more before and during the pandemic, after the pandemic they were more likely to work from home over commuting by car than people in lower income classes. As also concluded based on the results of the change in teleworking, age increases working from home over other modes of transport as the pandemic progresses. Older people are thus more likely to keep their working from home behaviour and thus work from home after the pandemic. The possession of a driver's license or a car causes in most cases a person to choose the car over teleworking, while it has a decreasing effect on the other modes of transportation. In the additional survey to the NVP, conducted at the start of the pandemic, people were asked about their productivity and pleasure while working from home. There is a clear relationship between productivity and working from home. People that experienced more productivity working from home were more likely to work from home during and after the pandemic rather than commuting. For pleasure, the results are more mixed, while in most cases even tending to a decreased likeability to work from home. For all modes, except cycling, probabilities were higher when a person lives in a single household.

The selection of characteristics showed thus many effects on working from home, the change in working from home and mode choice. Combining these results, it can be concluded that older, higher educated people living in less densely populated areas that work either in the ICT sector or have an office function have an increased likelihood to work from home. On the other hand, people with higher incomes working in industry or healthcare, who own a car and/or driver's license and who live in a single household are more likely to prefer commuting by car over teleworking.

3. *How can the impact of individual characteristics on mode choice be implemented in the model of Almere and* what changes in traffic intensities and *the commuting patterns* can be observed?

The COVID-19 pandemic caused people increased working from home, while also affecting the mode choice for commuting. In the answer to the previous research question, characteristics influencing teleworking and mode choice during different periods before, during and after the COVID-19 pandemic were analysed. For the period after the pandemic, when all measures taken by the government were lifted, a regression model is created that predicts mode choice based on characteristics of persons, their job and living location and their commuting trip. This regression model is implemented in the model of Almere to recalculate the modal split of the model. The modal split was calculated for each origin and destination pair of zones based on the characteristics of the origin and destination zone and the commuting trip between those zones. The recalculated modal split could then be used to generate mobility patterns that can be compared to the mobility patterns in a situation before the pandemic, which is already present in the model of Almere.

The implementation of teleworking in the model of Almere resulted in a reduction in traffic intensities. By implementing the regression model, the modal split for each origin-destination pair was recalculated and it was estimated that 15% of the total trips made in the model of Almere was replaced by teleworking. This was mainly at the expense of car and public transport use which respectively decreased from 63% to 52% and from 5% to 2%. Bicycle use slightly reduced from 32% to 30% due to the implementation of teleworking.

The reduction in traffic intensities could also be seen on the network. Both car and public transport intensities showed significant decreases during the morning hour. The biggest declines were observed the intensities of outgoing traffic for both modes. This is a direct result of residents of Almere who choose to work from home over commuting to their job outside of Almere. The highest absolute decreases in car intensities were visible on access roads to and from Almere and on the highway between Almere and Amsterdam. On the bridge between the two cities in the direction of Amsterdam, a decrease of 33% due to the implementation of teleworking was measured. Decreases between 40 and 60 per cent in public transport intensities were both seen on bus lines and train routes during the morning rush hour. Bicycle intensities did not show significant decreases and stayed about the same as before the implementation of teleworking. The differences in bicycle intensities on the network were mixed depending on the road. Mainly increases were observed on long continuous roads, which is the result of the recalculation of the modal split in which cyclists were more often assigned to longer distances than in the base model. On the other hand, bicycle use roads in the direction of the city centre and the train station decreased. The city centre and train station are attractive destinations for commuters and since teleworking decreases the number of commuting trips, decreases could be seen on these roads.

The results of this research thus indicate reductions in car use, due to the increase in working from home. These reductions also have influence on congestion and travel time. The Intensity-Capacity (IC) ratio is analysed as representation for congestion. This IC-ratio seemed to be dropped on most roads an alarming IC-ratio was indicated without the implementation of teleworking. Furthermore, the travel time to surrounding cities is estimated to determine the impact of the traffic intensity and congestion on the travel time for commuters. The results for the travel time show little decreases in travel time that are often below a minute. Only the travel time between Almere and Amsterdam decreased with just over a minute. In conclusion, it seems that teleworking both reduces traffic intensities and congestion, however, this has just a little impact on the travel times. The model used for these calculations is a static model and determines the travel times only on the intensity on and capacity of the roads. In reality, much more factors influence the travel time and thus a higher decrease in travel time can be expected due to increases in teleworking.

Teleworking is implemented in the model using a regression model based on observations of commuting trips made in the period just after the working from home advice was lifted. In this period, it was observed that people still work much from home. However, this will probably not remain forever and people are expected to return to commute to their offices again, although not necessarily as much as they did before the pandemic. To determine whether a decreased amount of teleworkers also benefits traffic intensities and congestion, a sensitivity analysis is performed. In this analysis, it was found that also to a lesser extent, teleworking can have a significant impact on congestion and traffic intensities. In a scenario where 50% of the current teleworking numbers are maintained, still decreases in travel time, traffic intensities and congestion can be observed. Ideally, at least 85% of the current days working from home should be maintained to reduce congestion between Almere and Amsterdam to a minimum.

What are the possible effects of teleworking on commuting patterns for residents of Almere?

By answering the four sub-questions, the research question can also be answered. During the pandemic, teleworking numbers increased and even after the pandemic, teleworking seemed to be an alternative to commuting. This was at the expense of the use of transportation modes car, public transport, bicycle and walking. People with characteristics such as living in a less densely populated area and having a higher received education were more often observed to be working from home. This was also the case for office workers and people living in a single house hold. On the other hand, people working in industry and health care decreased their commuting behaviour much less. Teleworking led to an estimated decrease in traffic intensities, especially for car and public transport. Moreover, a decrease in congestion and travel time for car traffic was observed due to the rise of teleworking. Even in future scenarios where teleworking is used to a lesser extent, it can still impact traffic intensities and commuting patterns. Working from home could thus be a solution to reduce traffic intensities, congestion, travel times.

8.2. Recommendations for future research

This research showed which characteristics determine whether someone commutes or works from home, but also that teleworking has impact on traffic intensities and commuting patterns. In the discussion, the limitations of this research are already indicated and in future research this can be addressed. A future research could for example perform a simulation of the population to increase accuracy of the implementation the regression model into the model of Almere. At the moment of the witing of this thesis, Goudappel is developing Octavius, a replacement fort he gravity model, which is used in this research. Octavius is a tour-based model that determines traffic flows based on individual behaviour. This model would be more suitable for the implementation of the regression model created in this research.

Moreover, the NVP data was not very representative for the inhabitants of Almere. A future research can either use a sample that corresponds more with the population of Almere or increase the scope of the study by looking beyond the city of Almere.

In this research, the effects of teleworking on mode choice, traffic intensities, congestion and travel time are investigated. However, there are many more secondary effects of teleworking, such as the impact on carbon dioxide and nitrogen emission, or on traffic safety.

Lastly, the data used in the research is gathered before, during and just after the pandemic. This offered the opportunity to analyse the differences in teleworking between the three periods. However, the used post-COVID data is gathered shortly after the measures were lifted. The use of more recent data could help to get an insight in teleworking effects in situations where less people are working from home.

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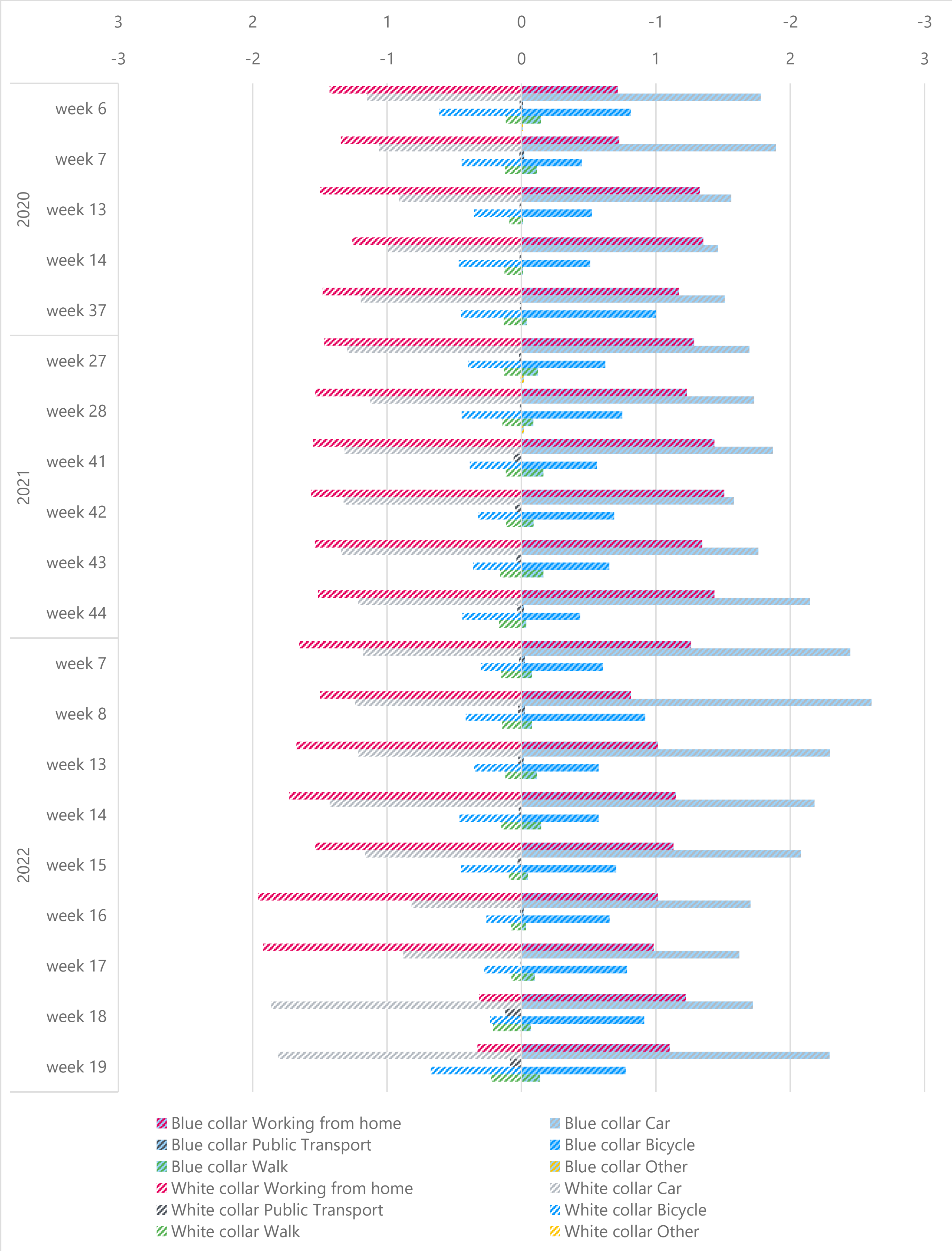
Appendix I Blue- and white-collar workers combined



Appendix II Correlations

In this research, regression analyses have been performed to determine the effects of individual characteristics on different teleworking statistics. Before performing these regression analyses, the correlations among the independent variables are checked to ensure that no independent is over-represented in the datasets. Since the multiple regression analyses made use of different datasets, the correlation in all datasets has been checked. The observed correlations in all datasets were fairly similar to the correlations in the other datasets. Therefore, only one table containing the correlations in a dataset is presented (Table 17). This table contains the correlations among the independent variables in the dataset that was used as input for the multinomial regression that determined the relationship between individual characteristics and the mode choice after the pandemic. Only the combinations of independent variables that have a value above 0.55 or -0.55 are considered correlated. Three pairs of independent variables can be seen in Table 17. Firstly, a correlation of -0.61 between higher and medium education was observed. However, both categories belong to the same independent variable. When a person received medium education, they can not have received also higher education. Furthermore, the correlation between income classes modal to two times modal and two times modal and higher is -0.57. These are also categories of the same independent variable and a person can not be in both groups. Lastly, the variables much less pleasure and much less productivity are correlated with a value of 0.57, meaning that there is a correlation between experiencing much less productivity and much less pleasure while working from home. The data gathered for these variables were gathered during the same survey. When a person is very negative towards working from home, they might fill in the lowest score for both of the questions. The opposite can be the case for much more pleasure and much more productive, which have a correlation of 0.49. Furthermore, other somewhat correlated variables are female and working in healthcare, driver's license and car ownership and higher education and high income. In the other datasets, similar correlations were found. In the final model used for the implementation in the model of Almere, there were also somewhat high correlations found between the variables explaining the sector or functions of the respondents. However, also here the correlations were within the same categorical variables.

Table 17 - Correlations between independent variables

	Industry	Construction	ICT	Healthcare	Office	Management	Research	Education	Lower education	Medium education	Higher education	Lower than modal	Modal to two times modal	Two times modal or higher	Gender	Low density	Medium density	High density	Driver's license	Car ownership
Industry	1																			
Construction	-0,21	1																		
ICT	-0,30	-0,17	1																	
Healthcare	-0,41	-0,29	-0,38	1																
Office	0,03	0,13	0,28	-0,23	1															
Management	0,12	0,16	0,14	-0,19	-0,41	1														
Research	0,12	-0,17	-0,29	0,15	-0,36	-0,19	1													
Education	-0,27	-0,14	-0,01	-0,03	-0,34	-0,18	-0,08	1												
Lower education	0,11	0,18	-0,11	-0,12	-0,11	-0,07	0,04	0,02	1											
medium education	0,03	0,05	-0,10	0,06	-0,02	-0,03	-0,16	-0,24	-0,37	1										
Higher education	-0,13	-0,10	0,14	-0,02	0,07	0,11	0,17	0,26	-0,42	-0,61	1									
Lower than modal	-0,15	0,08	-0,14	0,19	-0,16	-0,11	0,00	-0,28	0,08	0,16	-0,23	1								
Modal to two times modal	0,01	0,01	-0,16	0,07	0,00	-0,23	0,06	0,10	0,23	0,14	-0,26	-0,44	1							
Two times modal or higher	0,11	-0,07	0,23	-0,18	0,16	0,33	-0,06	0,07	-0,37	-0,21	0,42	-0,45	-0,57	1						
Gender	0,23	0,21	0,36	-0,46	0,06	0,19	0,04	-0,16	0,20	-0,09	-0,05	-0,29	-0,02	0,23	1					
Low density	0,04	0,17	-0,14	0,13	-0,06	-0,05	-0,13	-0,12	0,02	0,16	-0,15	0,09	0,08	-0,13	-0,09	1				
Medium density	-0,03	0,03	0,04	-0,05	0,06	-0,02	-0,10	0,19	-0,08	0,04	0,00	-0,07	-0,05	0,11	-0,02	-0,44	1			
High density	-0,01	-0,19	0,09	-0,08	0,02	0,06	0,17	-0,05	0,05	-0,16	0,13	-0,02	-0,03	0,04	0,10	-0,54	-0,51	1		
Driver's license	-0,02	0,29	0,00	-0,19	0,09	0,03	0,15	-0,11	0,31	-0,17	0,10	-0,04	0,04	0,01	0,14	0,16	0,01	-0,13	1	
Car ownership	0,04	0,31	-0,09	-0,21	-0,10	0,05	-0,08	0,25	0,30	-0,05	-0,15	-0,11	-0,05	0,06	0,12	0,17	0,16	-0,26	0,41	1
Single household	0,04	0,11	-0,13	-0,04	-0,01	-0,08	0,14	-0,16	0,04	-0,04	0,03	0,34	0,15	-0,40	-0,07	0,00	-0,12	0,08	0,19	-0,29
Household with children	-0,13	0,01	0,03	0,06	0,06	0,01	0,06	0,09	-0,05	-0,11	0,14	-0,21	-0,05	0,21	-0,06	-0,04	0,06	0,00	0,00	0,18
Adult household	0,09	-0,11	0,08	-0,03	-0,05	0,06	-0,17	0,05	0,02	0,15	-0,18	-0,11	-0,05	0,14	0,12	0,05	0,04	-0,07	-0,16	0,11
Much less pleasure	-0,05	0,00	-0,12	-0,09	-0,18	0,03	-0,13	0,33	0,03	-0,08	0,03	0,14	-0,08	0,01	-0,17	-0,17	0,13	0,02	-0,09	-0,11
Less pleasure	0,02	-0,22	0,01	0,04	0,00	0,04	0,02	0,05	0,10	-0,11	0,08	0,05	-0,04	0,01	-0,05	0,02	0,09	-0,08	0,11	-0,16
About the same pleasure	0,00	0,24	0,08	-0,04	0,04	0,07	-0,08	-0,13	-0,01	0,10	-0,08	-0,02	0,02	0,01	0,10	0,08	-0,08	0,01	-0,10	-0,08
More pleasure	-0,06	0,12	0,06	0,00	-0,01	0,06	0,30	-0,11	0,03	-0,02	0,02	-0,26	0,04	0,10	0,12	0,03	-0,23	0,14	-0,10	0,20
Much more pleasure	0,16	-0,22	-0,04	0,12	0,27	-0,29	-0,16	-0,19	-0,19	0,19	-0,09	0,06	0,10	-0,12	-0,03	0,05	0,10	-0,09	0,22	0,29
Much less productive	-0,05	0,08	-0,08	-0,10	-0,15	-0,01	0,00	0,22	-0,24	0,02	0,10	0,16	0,02	-0,10	-0,17	-0,06	0,11	-0,04	-0,19	-0,09
Less productive	-0,13	0,02	0,01	0,07	0,08	0,06	-0,15	-0,03	0,32	-0,03	-0,06	-0,05	0,06	-0,03	-0,04	0,09	-0,01	-0,06	0,35	0,03
About as productive	0,08	0,03	-0,01	-0,07	-0,01	0,04	0,09	-0,06	-0,16	0,05	0,04	-0,03	-0,03	0,06	0,09	-0,01	-0,14	0,11	-0,35	-0,05
More productive	-0,08	0,16	0,11	-0,05	-0,02	0,06	0,02	0,00	0,17	-0,01	-0,04	-0,05	-0,07	0,08	0,12	-0,06	-0,02	0,06	0,32	-0,04
Much more productive	0,15	-0,34	-0,05	0,18	0,11	-0,17	0,10	-0,10	-0,28	0,03	0,08	-0,04	0,00	0,02	-0,09	0,05	0,10	-0,12	-0,06	0,12

	Single household	Household with children	Adult household	Much less pleasure	Less pleasure	About the same pleasure	More pleasure	Much more pleasure	Much less productive	Less productive	About as productive	More productive	Much more productive
Industry													
Construction													
ICT													
Healthcare													
Office													
Management													
Research													
Education													
Lower education													
medium education													
Higher education													
Lower than modal													
Modal to two times modal													
Two times modal or higher													
Gender													
Low density													
Medium density													
High density													
Driver's license													
Car ownership													
Single household	1												
Household with children	-0,48	1											
Adult household	-0,49	-0,53	1										
Much less pleasure	0,17	-0,07	-0,08	1									
Less pleasure	-0,02	0,06	-0,05	-0,31	1								
About the same pleasure	-0,01	-0,01	0,02	-0,30	-0,32	1							
More pleasure	-0,11	0,07	0,03	-0,24	-0,29	-0,26	1						
Much more pleasure	-0,08	-0,07	0,15	-0,16	-0,22	-0,21	-0,14	1					
Much less productive	0,16	0,02	-0,17	0,57	-0,13	-0,32	-0,12	-0,04	1				
Less productive	-0,14	0,18	-0,06	0,11	0,20	-0,09	-0,10	-0,14	-0,24	1			
About as productive	0,04	-0,07	0,03	-0,16	0,07	0,19	-0,01	-0,16	-0,24	-0,29	1		
More productive	-0,03	-0,05	0,08	-0,28	0,06	0,14	0,09	-0,08	-0,24	-0,25	-0,29	1	
Much more productive	0,03	-0,07	0,04	-0,19	-0,19	-0,01	0,12	0,49	-0,18	-0,24	-0,25	-0,25	1

Appendix III Multinomial regression results

In this appendix, the results of the regression analyses for mode choice will be displayed. The tables with the results do not include the reference levels of the independent variables. These are therefore presented in Table 18.

Table 18 - List of independent variables with their reference categories

C	*Independent Variable*	*Reference category*
	intercept	
	travel time	
Sector	industry	no
	construction	no
	ICT	no
	healthcare	no
Function	office	no
	management	no
	research	no
	education	no
	higher education	lower education
	medium education	lower education
	modal to two times modal	lower than modal
	two times modal or higher	lower than modal
	age	
	gender	female
	high density	low density
	medium density	low density
	household size	
	driver's license	no
	car ownership	no
Pleasure	more	much less
	less	much less
	about the same	much less
	much more	much less
Productivity	more	much less
	less	much less
	about the same	much less
	much more	much less
House hold	adult	single
	with children	single
	accessibility	

Table 19 – Regression results for weeks before the pandemic (from left to right: car, bicycle, walking, public transport (ref = teleworking))

C	Variable	β	Std. Error	P-value
	intercept	-3,81	0,812	0,000 ***
	travel time	-0,05	0,291	0,861
Sector	industry	0,00	0,258	0,990
	construction	1,04	0,500	0,037 *
	ICT	-0,13	0,263	0,625
	healthcare	-0,26	0,201	0,191
Function	office	0,67	0,178	0,000 ***
	management	-0,18	0,231	0,444
	research	0,10	0,530	0,857
	education	0,46	0,316	0,149
	higher education	1,02	0,403	0,012 *
	medium education	0,45	0,395	0,250
	modal to two times	0,89	0,265	0,001 ***
	two times modal or	0,90	0,301	0,003 **
	age	0,00	0,007	0,666
	gender (male)	-0,09	0,153	0,546
	high density	-0,89	0,190	0,000 ***
	medium density	-0,75	0,234	0,001 **
	household size	-0,02	0,104	0,846
	driver's license	2,04	0,367	0,000 ***
	car ownership	1,63	0,327	0,000 ***
Pleasure	more	-0,26	0,336	0,440
	less	-0,70	0,245	0,004 **
	about the same	-0,27	0,265	0,317
	much more	-1,36	0,361	0,000 ***
Productivity	more	1,97	0,292	0,000 ***
	less	1,11	0,248	0,000 ***
	about the same	1,43	0,257	0,000 ***
	much more	1,03	0,302	0,001 ***
House hold	adult	-0,03	0,254	0,910
	with children	0,12	0,348	0,728
	accessibility	0,04	0,061	0,497

B	Variable	β	Std. Error	P-value
	intercept	-4,19	0,959	0,000 ***
	travel time	-3,12	0,425	0,000 ***
Sector	industry	-0,31	0,296	0,299
	construction	-0,98	0,775	0,205
	ICT	-0,16	0,298	0,582
	healthcare	-0,73	0,250	0,003 **
Function	office	1,70	0,235	0,000 ***
	management	0,48	0,307	0,118
	research	0,84	0,631	0,181
	education	0,98	0,392	0,012 *
	higher education	1,29	0,508	0,011 *
	medium education	0,85	0,503	0,090 .
	modal to two times	0,61	0,314	0,053 .
	two times modal or	0,57	0,348	0,104
	age	0,01	0,009	0,144
	gender (male)	0,00	0,176	0,983
	high density	-0,01	0,229	0,957
	medium density	-0,30	0,277	0,287
	household size	0,21	0,117	0,070 .
	driver's license	1,24	0,448	0,005 **
	car ownership	-1,18	0,309	0,000 ***
Pleasure	more	-1,07	0,391	0,006 **
	less	-0,63	0,284	0,025 *
	about the same	-0,45	0,305	0,143
	much more	-1,64	0,423	0,000 ***
Productivity	more	2,22	0,343	0,000 ***
	less	1,40	0,302	0,000 ***
	about the same	1,69	0,310	0,000 ***
	much more	1,45	0,359	0,000 ***
House hold	adult	0,45	0,300	0,134
	with children	0,45	0,402	0,258
	accessibility	0,03	0,070	0,619

W	Variable	β	Std. Error	P-value
	intercept	-4,82	1,202	0,000 ***
	travel time	0,25	0,394	0,520
Sector	industry	-0,86	0,455	0,058 .
	construction	0,71	0,615	0,248
	ICT	-0,99	0,408	0,015 *
	healthcare	-0,13	0,330	0,703
Function	office	1,06	0,307	0,001 ***
	management	-0,06	0,423	0,887
	research	-8,01	0,000	0,000 ***
	education	0,68	0,497	0,169
	higher education	0,53	0,523	0,308
	medium education	-0,92	0,530	0,081 .
	modal to two times	-0,01	0,386	0,974
	two times modal or	0,14	0,425	0,734
	age	0,01	0,011	0,197
	gender (male)	0,40	0,235	0,092
	high density	0,42	0,328	0,198
	medium density	0,09	0,408	0,829
	household size	-0,05	0,157	0,727
	driver's license	-0,42	0,463	0,362
	car ownership	0,25	0,393	0,519
Pleasure	more	0,77	0,565	0,171
	less	0,66	0,454	0,147
	about the same	1,34	0,473	0,005 **
	much more	1,01	0,615	0,101
Productivity	more	1,79	0,496	0,000 ***
	less	1,64	0,466	0,000 ***
	about the same	1,84	0,463	0,000 ***
	much more	0,72	0,552	0,190
House hold	adult	-0,35	0,367	0,335
	with children	-0,45	0,524	0,391
	accessibility	0,14	0,092	0,124

PT	Variable	β	Std. Error	P-value
	intercept	-20,06	1,605	0,000 ***
	travel time	1,52	0,588	0,010 **
Sector	industry	-6,05	0,004	0,000 ***
	construction	1,03	1,191	0,385
	ICT	-0,39	0,496	0,429
	healthcare	-0,07	0,688	0,913
Function	office	2,69	1,074	0,012 *
	management	2,85	1,134	0,012 *
	research	-1,21	0,031	0,000 ***
	education	-4,21	0,043	0,000 ***
	higher education	6,36	0,824	0,000 ***
	medium education	4,13	0,887	0,000 ***
	modal to two times	-0,29	1,124	0,797
	two times modal or	0,76	1,107	0,491
	age	0,06	0,020	0,002 **
	gender (male)	0,04	0,393	0,921
	high density	-0,76	0,699	0,277
	medium density	-1,02	0,740	0,168
	household size	0,66	0,229	0,004 **
	driver's license	0,70	0,973	0,470
	car ownership	-1,24	0,628	0,048 *
Pleasure	more	-0,40	0,725	0,577
	less	-0,32	0,558	0,562
	about the same	-1,49	0,696	0,033 *
	much more	-7,23	0,009	0,000 ***
Productivity	more	1,44	0,800	0,072 .
	less	1,03	0,779	0,184
	about the same	1,22	0,783	0,120
	much more	1,23	0,885	0,164
House hold	adult	-0,59	0,704	0,403
	with children	-1,49	0,954	0,119
	accessibility	1,02	0,227	0,000 ***

Table 20 - Regression results for weeks during the first weeks of the pandemic (from left to right: car, bicycle, walking, public transport (ref = teleworking))

C	Variable	β	Std. Error	P-value
	intercept	-2,86	1,234	0,020 *
	travel time	0,65	0,239	0,006 **
Sector	industry	0,83	0,188	0,000 ***
Sector	construction	0,20	0,323	0,535
Sector	ICT	-0,70	0,250	0,005 **
Sector	healthcare	0,60	0,184	0,001 **
Function	office	-0,93	0,165	0,000 ***
Function	management	0,13	0,201	0,518
Function	research	-1,57	0,572	0,006 **
Function	education	0,10	0,268	0,708
	higher education	-1,47	0,334	0,000 ***
	medium education	-0,67	0,325	0,039 *
	modal to two times modal	0,67	0,320	0,037 *
	two times modal or higher	0,75	0,335	0,025 *
	age	0,00	0,007	0,521
	gender (male)	-0,04	0,128	0,764
	high density	-0,06	0,152	0,714
	medium density	0,42	0,191	0,030 *
	household size	0,02	0,087	0,774
	driver's license	-0,72	0,342	0,036 *
	car ownership	3,26	1,021	0,001 **
Pleasure	more	0,16	0,296	0,596
Pleasure	less	0,45	0,212	0,033 *
Pleasure	about the same	0,23	0,227	0,319
Pleasure	much more	1,07	0,359	0,003 **
Productivity	more	-0,25	0,251	0,325
Productivity	less	-0,52	0,237	0,027 *
Productivity	about the same	-0,21	0,238	0,375
Productivity	much more	-0,42	0,292	0,149
House hold	adult	-0,37	0,220	0,089 .
House hold	with children	-0,20	0,295	0,498
	accessibility	-0,05	0,052	0,353

B	Variable	β	Std. Error	P-value
	intercept	-12,68	0,971	0,000 ***
	travel time	-2,49	0,745	0,001 ***
Sector	industry	0,60	0,342	0,077 .
Sector	construction	-9,99	0,000	0,000 ***
Sector	ICT	-1,31	0,548	0,017 *
Sector	healthcare	0,60	0,276	0,030 *
Function	office	0,02	0,299	0,960
Function	management	0,28	0,412	0,497
Function	research	-9,51	0,000	0,000 ***
Function	education	1,06	0,405	0,009 **
	higher education	9,63	0,488	0,000 ***
	medium education	10,41	0,509	0,000 ***
	modal to two times modal	-0,47	0,348	0,173
	two times modal or higher	-0,78	0,378	0,040 *
	age	0,00	0,010	0,771
	gender (male)	0,34	0,215	0,113
	high density	1,04	0,299	0,001 ***
	medium density	0,36	0,398	0,360
	household size	-0,17	0,150	0,246
	driver's license	1,58	1,134	0,163
	car ownership	-1,17	0,409	0,004 **
Pleasure	more	-9,84	0,000	0,000 ***
Pleasure	less	0,15	0,370	0,689
Pleasure	about the same	0,03	0,382	0,928
Pleasure	much more	-0,09	0,660	0,897
Productivity	more	-0,13	0,464	0,784
Productivity	less	-0,19	0,453	0,672
Productivity	about the same	0,26	0,436	0,549
Productivity	much more	-0,08	0,539	0,879
House hold	adult	1,54	0,421	0,000 ***
House hold	with children	1,84	0,543	0,001 ***
	accessibility	-0,22	0,088	0,012 *

W	Variable	β	Std. Error	P-value
	intercept	-16,73	1,672	0,000 ***
	travel time	-0,19	0,812	0,814
Sector	industry	-0,09	0,853	0,920
Sector	construction	-0,08	1,130	0,940
Sector	ICT	-1,85	1,083	0,087 .
Sector	healthcare	-1,59	0,941	0,091 .
Function	office	-0,89	0,672	0,186
Function	management	1,84	0,729	0,012 *
Function	research	-6,45	0,000	0,000 ***
Function	education	0,47	0,883	0,593
	higher education	11,06	0,810	0,000 ***
	medium education	10,30	0,930	0,000 ***
	modal to two times modal	-1,16	0,708	0,102
	two times modal or higher	-1,43	0,784	0,068 .
	age	0,04	0,021	0,053 .
	gender (male)	-0,06	0,423	0,881
	high density	0,78	0,632	0,216
	medium density	1,96	0,642	0,002 **
	household size	0,21	0,241	0,381
	driver's license	0,50	1,335	0,708
	car ownership	-2,35	0,671	0,000 ***
Pleasure	more	-9,15	0,001	0,000 ***
Pleasure	less	1,03	0,859	0,230
Pleasure	about the same	1,17	0,913	0,201
Pleasure	much more	2,91	1,192	0,015 *
Productivity	more	0,33	1,201	0,786
Productivity	less	1,30	1,142	0,255
Productivity	about the same	1,84	1,131	0,103
Productivity	much more	-1,07	1,636	0,512
House hold	adult	-0,14	0,799	0,864
House hold	with children	0,24	0,963	0,801
	accessibility	-0,02	0,170	0,884

PT	Variable	β	Std. Error	P-value
	intercept	-1,03	0,012	0,000 ***
	travel time	1,96	0,617	0,001 **
Sector	industry	-0,44	0,108	0,000 ***
Sector	construction	-0,13	0,000	0,000 ***
Sector	ICT	-0,48	0,015	0,000 ***
Sector	healthcare	-0,67	0,631	0,286
Function	office	1,79	0,019	0,000 ***
Function	management	-0,69	0,003	0,000 ***
Function	research	-0,06	0,000	0,000 ***
Function	education	-1,35	0,000	0,000 ***
	higher education	-4,02	0,020	0,000 ***
	medium education	3,09	0,032	0,000 ***
	modal to two times modal	-2,90	0,902	0,001 **
	two times modal or higher	-2,22	0,018	0,000 ***
	age	-0,04	0,862	0,966
	gender (male)	-2,79	0,659	0,000 ***
	high density	0,82	1,179	0,487
	medium density	-0,72	0,040	0,000 ***
	household size	-3,66	1,657	0,027 *
	driver's license	-0,92	0,012	0,000 ***
	car ownership	0,25	0,033	0,000 ***
Pleasure	more	-0,45	0,638	0,482
Pleasure	less	-3,45	0,714	0,000 ***
Pleasure	about the same	-1,35	0,220	0,000 ***
Pleasure	much more	5,19	1,666	0,002 **
Productivity	more	2,65	0,341	0,000 ***
Productivity	less	-1,18	0,040	0,000 ***
Productivity	about the same	-1,33	0,126	0,000 ***
Productivity	much more	-0,65	0,119	0,000 ***
House hold	adult	-1,72	0,005	0,000 ***
House hold	with children	3,38	1,659	0,041 *
	accessibility	-1,22	4,863	0,802

Table 21 - Regression results for all weeks during the pandemic (from left to right: car, bicycle, walking, public transport (ref = teleworking)) (number of observations: 9294)

C	Variable	β	Std. Error	P-value
	intercept	2,15	0,383	0,000 ***
	travel time	0,72	0,115	0,000 ***
Sector	industry	0,52	0,094	0,000 ***
	construction	0,47	0,174	0,007 **
	ICT	-0,56	0,103	0,000 ***
	healthcare	0,18	0,091	0,048 *
Function	office	-0,85	0,079	0,000 ***
	management	-0,26	0,102	0,010 **
	research	-0,84	0,240	0,000 ***
	education	0,05	0,136	0,687
	higher education	-1,69	0,180	0,000 ***
	medium education	-0,99	0,177	0,000 ***
	modal to two times modal	0,50	0,146	0,001 ***
	two times modal or higher	0,63	0,153	0,000 ***
	age	-0,02	0,003	0,000 ***
	gender (male)	-0,05	0,060	0,396
	high density	0,01	0,072	0,905
	medium density	0,27	0,093	0,003 **
	household size	-0,01	0,040	0,736
	driver's license	0,58	0,204	0,005 **
	car ownership	0,43	0,152	0,004 **
Pleasure	more	0,33	0,134	0,013 *
	less	0,26	0,102	0,010 *
	about the same	0,27	0,106	0,010 **
	much more	0,92	0,160	0,000 ***
Productivity	more	-0,80	0,119	0,000 ***
	less	-1,00	0,110	0,000 ***
	about the same	-0,73	0,111	0,000 ***
	much more	-1,03	0,133	0,000 ***
House hold	adult	-0,33	0,102	0,001 **
	with children	-0,02	0,138	0,859
	accessibility	-0,16	0,025	0,000 ***

B	Variable	β	Std. Error	P-value
	intercept	-2,54	0,661	0,000 ***
	travel time	-3,66	0,318	0,000 ***
Sector	industry	0,36	0,149	0,017 *
	construction	-1,59	0,729	0,029 *
	ICT	-0,89	0,163	0,000 ***
	healthcare	0,15	0,136	0,261
Function	office	-0,29	0,125	0,018 *
	management	-0,15	0,177	0,405
	research	-1,56	0,731	0,032 *
	education	0,38	0,208	0,067 .
	higher education	-0,40	0,316	0,206
	medium education	0,18	0,318	0,576
	modal to two times modal	0,00	0,195	0,996
	two times modal or higher	0,17	0,206	0,405
	age	-0,01	0,005	0,075 .
	gender (male)	0,38	0,092	0,000 ***
	high density	0,40	0,127	0,002 **
	medium density	0,68	0,149	0,000 ***
	household size	-0,05	0,065	0,420
	driver's license	1,84	0,434	0,000 ***
	car ownership	-1,10	0,148	0,000 ***
Pleasure	more	-0,58	0,218	0,007 **
	less	0,09	0,136	0,523
	about the same	-0,14	0,145	0,339
	much more	-0,06	0,251	0,814
Productivity	more	-0,66	0,184	0,000 ***
	less	-0,25	0,161	0,119
	about the same	-0,15	0,165	0,379
	much more	-0,44	0,196	0,025 *
House hold	adult	0,04	0,160	0,800
	with children	0,47	0,218	0,030 *
	accessibility	0,15	0,040	0,000 ***

W	Variable	β	Std. Error	P-value
	intercept	-8,86	0,557	0,000 ***
	travel time	-1,16	0,367	0,002 **
Sector	industry	-0,33	0,310	0,281
	construction	-1,28	1,027	0,211
	ICT	-0,86	0,260	0,001 ***
	healthcare	-0,08	0,247	0,735
Function	office	-0,35	0,213	0,104
	management	0,26	0,275	0,341
	research	-1,04	1,073	0,335
	education	0,38	0,313	0,225
	higher education	6,93	0,288	0,000 ***
	medium education	6,85	0,293	0,000 ***
	modal to two times modal	0,59	0,430	0,167
	two times modal or higher	0,37	0,450	0,410
	age	-0,02	0,007	0,019 *
	gender (male)	0,46	0,159	0,004 **
	high density	1,01	0,235	0,000 ***
	medium density	1,38	0,264	0,000 ***
	household size	0,16	0,099	0,109
	driver's license	-0,41	0,432	0,340
	car ownership	-0,77	0,242	0,001 **
Pleasure	more	-0,49	0,374	0,188
	less	-0,21	0,213	0,313
	about the same	-0,11	0,231	0,649
	much more	-0,30	0,479	0,531
Productivity	more	-0,46	0,374	0,223
	less	0,93	0,298	0,002 **
	about the same	0,84	0,312	0,007 **
	much more	-0,11	0,399	0,786
House hold	adult	-0,76	0,257	0,003 **
	with children	-0,81	0,356	0,022 *
	accessibility	-0,06	0,067	0,383

PT	Variable	β	Std. Error	P-value
	intercept	-16,72	1,741	0,000 ***
	travel time	-0,98	0,855	0,253
Sector	industry	-3,42	0,479	0,000 ***
	construction	-3,27	0,120	0,000 ***
	ICT	-0,51	0,580	0,381
	healthcare	2,22	0,493	0,000 ***
Function	office	-0,04	0,627	0,951
	management	-0,02	0,777	0,981
	research	-0,52	0,151	0,001 ***
	education	-0,27	3,898	0,945
	higher education	0,93	1,177	0,431
	medium education	2,27	1,202	0,059 .
	modal to two times modal	-0,75	1,147	0,511
	two times modal or higher	1,06	1,066	0,319
	age	0,05	0,024	0,020 *
	gender (male)	1,08	0,511	0,034 *
	high density	3,63	2,411	0,132
	medium density	4,92	2,413	0,041 *
	household size	0,17	0,292	0,569
	driver's license	-1,96	1,021	0,055 .
	car ownership	-1,40	0,591	0,018 *
Pleasure	more	3,11	2,727	0,254
	less	6,78	1,207	0,000 ***
	about the same	5,67	1,228	0,000 ***
	much more	5,94	1,613	0,000 ***
Productivity	more	-3,70	0,860	0,000 ***
	less	-3,50	0,911	0,000 ***
	about the same	-2,59	0,791	0,001 **
	much more	-7,02	4,224	0,097 .
House hold	adult	-0,80	0,670	0,232
	with children	-2,03	1,033	0,049 *
	accessibility	0,58	0,210	0,006 **

Table 22 - Regression results for weeks after the pandemic (from left to right: car, bicycle, walking, public transport (ref = teleworking)) (number of observations: 9294)

C	Variable	β	Std. Error	P-value
	intercept	2.417	0.489	0,000 ***
	travel time	0.961	0.135	0,000 ***
Sector	industry	0.700	0.106	0,000 ***
Sector	construction	-0.452	0.194	0,020 *
Sector	ICT	-0.399	0.123	0,001 **
Sector	healthcare	0.913	0.107	0,000 ***
Function	office	-0.278	0.095	0,003 **
Function	management	0.669	0.128	0,000 ****
Function	research	1.044	0.332	0,002 **
Function	education	0.047	0.165	0,777
	higher education	-1.295	0.251	0,000 ***
	medium education	-0.451	0.249	0,071 .
	modal to two times modal	-0.201	0.156	0,197
	two times modal or higher	-0.268	0.163	0,102
	age	-0.019	0.004	0,000 ***
	gender (male)	0.369	0.072	0,000 ***
	high density	0.240	0.089	0,007 **
	medium density	0.639	0.109	0,000 ***
	household size	-0.073	0.047	0,123
	driver's license	0.146	0.268	0,585
	car ownership	0.298	0.152	0,050 *
Pleasure	more	0.499	0.164	0,002 **
Pleasure	less	0.192	0.121	0,113
Pleasure	about the same	-0.034	0.127	0,792
Pleasure	much more	0.534	0.179	0,003 **
Productivity	more	-0.603	0.144	0,000 ***
Productivity	less	-0.836	0.136	0,000 ***
Productivity	about the same	-0.684	0.137	0,000 ***
Productivity	much more	-0.630	0.155	0,000 ***
House hold	adult	-0.575	0.119	0,000 ***
House hold	with children	0.139	0.161	0,388
	accessibility	-0.193	0.029	0,000 ***

B	Variable	β	Std. Error	P-value
	intercept	1.082	0.649	0,095 .
	travel time	-2.604	0.287	0,000 ***
Sector	industry	0.059	0.161	0,713
Sector	construction	-16.528	0.000	0,000 ***
Sector	ICT	-0.336	0.163	0,039 *
Sector	healthcare	0.562	0.141	0,000 ***
Function	office	0.249	0.127	0,050 .
Function	management	0.711	0.178	0,000 ***
Function	research	-0.536	1.044	0,608
Function	education	-0.281	0.271	0,298
	higher education	-0.241	0.396	0,542
	medium education	1.035	0.398	0,009 **
	modal to two times modal	-0.904	0.181	0,000 ***
	two times modal or higher	-0.097	0.190	0,611
	age	-0.009	0.005	0,077 .
	gender (male)	0.175	0.094	0,062 .
	high density	0.805	0.138	0,000 ***
	medium density	1.040	0.160	0,000 ***
	household size	-0.272	0.068	0,000 ***
	driver's license	-0.168	0.303	0,579
	car ownership	-0.870	0.155	0,000 ***
Pleasure	more	-0.326	0.220	0,138
Pleasure	less	0.057	0.145	0,695
Pleasure	about the same	-0.389	0.153	0,011 **
Pleasure	much more	-1.125	0.309	0,000 ***
Productivity	more	-1.095	0.190	0,000 ***
Productivity	less	-0.658	0.168	0,000 ***
Productivity	about the same	-0.600	0.169	0,000 ***
Productivity	much more	-0.691	0.203	0,001 ***
House hold	adult	0.040	0.164	0,806
House hold	with children	0.897	0.226	0,000 ***
	accessibility	-0.060	0.040	0,128

W	Variable	β	Std. Error	P-value
	intercept	-14.577	0.552	0,000 ***
	travel time	-0.344	0.313	0,271
Sector	industry	-0.091	0.265	0,732
Sector	construction	-0.118	0.574	0,837
Sector	ICT	-0.647	0.316	0,040 *
Sector	healthcare	-0.003	0.298	0,992
Function	office	0.966	0.264	0,000 ***
Function	management	1.527	0.343	0,000 ***
Function	research	0.649	1.054	0,538
Function	education	0.664	0.389	0,088 .
	higher education	11.479	0.278	0,000 ***
	medium education	12.062	0.294	0,000 ***
	modal to two times modal	0.023	0.375	0,952
	two times modal or higher	0.000	0.389	1,000
	age	-0.016	0.008	0,031 *
	gender (male)	-0.073	0.148	0,623
	high density	0.986	0.244	0,000 ***
	medium density	0.169	0.314	0,591
	household size	0.289	0.110	0,009 **
	driver's license	-1.615	0.344	0,000 ***
	car ownership	-0.062	0.262	0,814
Pleasure	more	-0.980	0.347	0,005 **
Pleasure	less	-0.650	0.237	0,006 **
Pleasure	about the same	-0.832	0.252	0,001 ***
Pleasure	much more	-0.669	0.397	0,092 .
Productivity	more	0.620	0.367	0,091 .
Productivity	less	0.547	0.332	0,100 .
Productivity	about the same	1.142	0.326	0,000 ***
Productivity	much more	0.800	0.372	0,031 *
House hold	adult	-0.580	0.246	0,019 *
House hold	with children	-1.241	0.376	0,001 ***
	accessibility	0.201	0.068	0,003 **

PT	Variable	β	Std. Error	P-value
	intercept	-16.225	1.230	0,000 ***
	travel time	1.081	1.347	0,422
Sector	industry	-1.699	4.307	0,693
Sector	construction	-0.550	0.062	0,000 ***
Sector	ICT	-5.122	3.656	0,161
Sector	healthcare	3.870	1.503	0,010 *
Function	office	6.695	1.581	0,000 ***
Function	management	8.439	1.761	0,000 ***
Function	research	2.895	0.009	0,000 ***
Function	education	4.125	0.220	0,000 ***
	higher education	0.270	0.996	0,786
	medium education	0.165	0.915	0,857
	modal to two times modal	-1.516	1.450	0,296
	two times modal or higher	-2.235	1.912	0,243
	age	-0.108	0.052	0,037 *
	gender (male)	1.089	0.976	0,264
	high density	-0.027	2.167	0,990
	medium density	-0.307	2.087	0,883
	household size	2.499	0.821	0,002 **
	driver's license	-6.879	1.750	0,000 ***
	car ownership	-1.177	1.231	0,339
Pleasure	more	-0.402	0.802	0,616
Pleasure	less	2.490	1.777	0,161
Pleasure	about the same	0.904	1.460	0,536
Pleasure	much more	4.615	2.130	0,030 *
Productivity	more	0.404	1.473	0,784
Productivity	less	1.138	1.517	0,453
Productivity	about the same	1.946	1.339	0,146
Productivity	much more	-4.670	1.875	0,013 *
House hold	adult	-3.610	1.584	0,023 *
House hold	with children	-10.847	2.875	0,000 ***
	accessibility	1.855	0.449	0,000 ***

Appendix IV Standardized coefficients

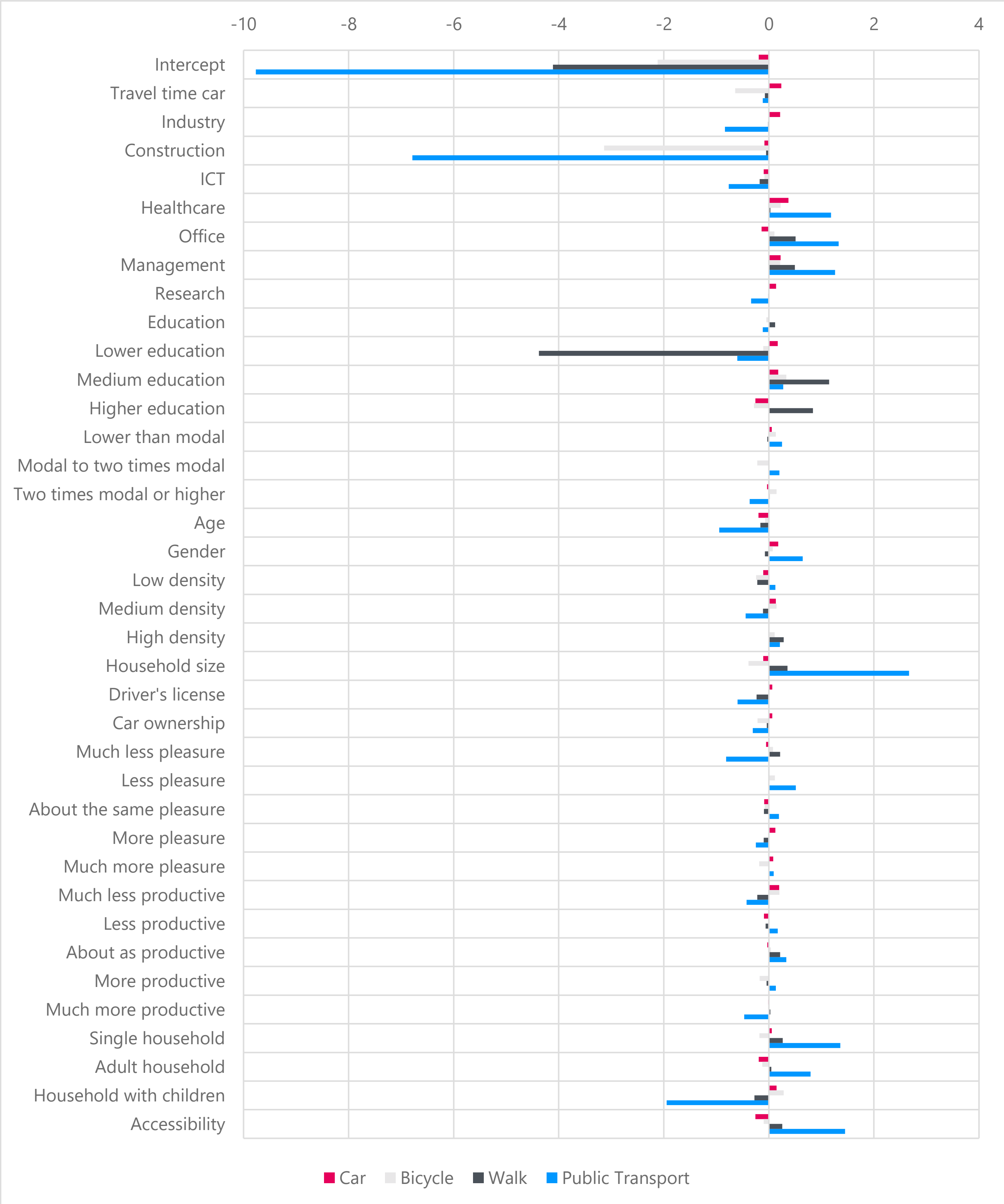


Figure 20 - Standardized coefficients