The impact of the COVID-19 pandemic on individual's travel activities and variations with social status and spatial settings:

A study based on Dutch National Travel Survey (ODiN)

By

Xiaoyang Wu

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Supervisor: Prof. Dr. Ir. Dick Ettema

Summary

The COVID-19 has posed great challenges to the human community since its first appearance. Governments generally took drastic measures to contain the spread of virus. The restrictive measures and fear of contagion led to an overall reduction in mobility of all modalities around the world, including the Netherlands. The pandemic also changed people's daily activity patterns, which can be reflected by travel purposes, but there is only limited research focused on this area. Besides, literature has revealed that the disadvantaged group (low-income, ethnic minority, disabled, etc.) had suffered more than the majority of the society, so it is also interesting to find out whether such social disparity existed in the Netherlands. Therefore, the main research question is proposed:

Did the COVID-19 pandemic significantly influenced people's travel activities and did the impacts varied with income and urban-rural settings of residence?

(*by "travel activity" I mean the outdoor activities linked with daily travel purposes)

The thesis uses the results of Dutch National Travel Survey *(Onderweg in Nederland, ODiN)* of year 2019 and 2020. The survey follows a strict framework, includes extensive aspects of travel characteristics, and covers a large representative sample, and thus is a reliable data source. After data cleaning, 44959 and 53500 adult respondents were drawn from the year of 2019 and 2020, respectively.

Four major types of travel purposes were studied: **work-related, leisure, shopping, and visit/stay**. By descriptive analysis, it is observed that the reduction of mobility was full-scale across all travel purposes and that the activity diversity shrank, from 1.18 travel purposes engaged per person per day to only 1.01 per day. As for relative share, work travel saw a 6.70% decrease, while shopping increased 4.38%.

Within this study the ***'travel probability'*** is *defined as* the ratio of number of people travelled for the given purpose to the total number of respondents in the sample (fraction). Changes of average distance, time travelled, and travel probability were plotted in several line graphs by every travel purpose and the variation with income and urbanization levels were also examined. Overall, work travel was the most negatively impacted, shopping travel stayed stable to a large extent, and visit travel, the least frequent activity, was also strongly impacted. Among people who travelled outdoors, leisure travel distance decreased in two waves of the pandemic outbreak compared to last year, but its average travel time was longer in all month-groups of 2020, suggesting possible change of people's recreational travel behaviour to neighbourhood walking. The varied impact of pandemic in income levels was most noticeable in work travel, but for other travel purposes the patterns were not as clear. Variations with urbanity levels were even smaller. Thus, it was *assumed* income and urbanity levels would not have significant impacts on leisure, shopping, and visiting travel, but the pandemic *would*.

However, results of binary logistic regression models on travel probability for each travel purpose partly denied the *assumption* above. The urbanization classes best explained shopping travel probability, and partly explained work and visit travel probability. Income level was not as a good predictor as expected. It could significantly impact leisure and visit travel, and partly affect work travel. Level of education was a much better parameter predicting travel probability for all travel purposes that could also reveal disparity in social status. Yet, the model showed perfect goodness of fit when interpreting work travel patterns.

By adding interaction terms between disparity indices of interest (income, education, and urbanity levels) and month-groups (reflecting policy changes in different stages of pandemic) to regression models, significant improvements from basic models were found for work and shopping. Respondents living in the most strongly urbanized cities (*U1*) and with higher level of education *(EDU3)* were two factors that their influence on work travel probability depended significantly on the pandemic's effects. The effects of middle- and high-level of education on shopping travel probability also showed significant dependency on the first wave of the outbreak. No significant improvements were found in leisure or visit travel models, so the impacts socio-demographic factors on leisure and visit travel probability were independent from the pandemic.

This thesis has several limitations with regard to sample weighting, survey designs, model goodness of fit, and choice of variables and models. But it also contributes to the understanding to the change of travel activities under the pandemic's conditions in the Dutch context. The thesis also revealed potential supressed travel demand among low-income people as well as their limited accessibility to good-quality shopping sites (supermarkets or malls) and attached importance to built environment of neighbourhoods. Future research can further investigate the impact of different stages of the pandemic by adding data from year 2021 and 2022.

Key words: COVID-19, pandemic impact on mobility, travel behaviour/ travel patterns, travel activity, travel purposes, Dutch National Travel Survey (ODiN), income, urbanization level (urbanity level), level of education, social disparity, interaction effects

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Preface

This thesis aims at revealing the changes of daily activities and related travel purposes during the first two waves of COVID-19 outbreak in the Netherlands in 2020 to fill the research gaps in relating areas. With this thesis, I conclude my MSc programme in Human Geography at Utrecht University.

I am thankful to my supervisor, Dick Ettema, for inspiring me to choose COVID-19 as my main research topic. At the time, most western countries had gone through the Omicron crisis and begun to reopen the borders and release nearly all the mandatory measures. Thus, it was a perfect time to look back on how the pandemic impacted fundamentally on human society, especially from the perspective of mobility, and draw implications for future policy making.

The impact of COVID-19 was profound on all aspects. It was sad that COVID-19 pandemic indeed tore the society apart to some extent. People protested pandemic controls for freedom. Increasing hate crimes aimed at East Asians were seen around the world over last two years. As for health impacts, the infected cases kept rising and falling, making vulnerable people fear from time to time and resulting in mental problems. The economic impact was also significant. The supply chain disrupted, and a shortage of chips was witnessed.

From my own perspective, when I flew to the Netherlands in August last year, I did not expect going through such a hard time that I was always depressed by news happening every day. Not only was I fearing of contagion that might add to the difficulty for me to get back home, but I was also disappointed by disgusting news, such as the Ukraine-Russian war as well as Shanghai Lockdown.

However, I was lucky enough to have friends standing behind who eased my tensions during those lonely nights. Therefore, first of all, I would like to thank all my friends, Chuyin, Zhiming, Boyan, Fengyuan, Dingyi, Haifeng, and so forth, for their support. I would also like to thank my supervisor, Dick Ettema, for his words that played a key role in getting me back on track, "There are many things that are beyond our controls. Just focus on things that you can control, and this will make you happier".

As for the thesis, I also challenge myself to go through all the materials independently and to try 'new' techniques that I always wanted to learn but lacked the chance to practice. Thus, I would like to thank myself for the efforts that I have paid since February. Most importantly, I want to express my gratitude to Dr. Yang Hu, who helped me begin with data analysis and clarify my thoughts; to Dr. Dea van Lierop who provides precious suggestions in mid-term presentation; to Prof. Ettema for weekly meetings to track my progress during the summer holiday. Also thank Qiliang, Han, and Stack Overflow for solving my R questions during data analysis. Without your help I could not have made it. Lastly, I shall thank my parents for supporting me to pursue my degree abroad both financially and mentally. Love you so much! This thesis is the best gift to you!

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1. Introduction

1.1. Research background

The COVID-19 pandemic posed great challenges to the world since its emergence in Wuhan, China in late 2019. It hit the economy hard, worsened people's health both physically and mentally and made the society more divided. Though the virus seems not scary to many people now, this contagious virus had aroused panic in its first appearance in many countries, which forced governments around the world to take drastic measures to contain the outbreak. Despite differences in cultural and political contexts, the policies carried out in different countries were largely the same (as the primary goals for most governments were to reduce excess deaths and prevent hospitals from being overwhelmed), including mandatory masks, social distancing, suggestion of remote working (WFH), and closure of (inessential) contact-based businesses and curfews to supress physical contacts especially gatherings for leisure.

According to literature, there is a two-way interaction between the pandemic and mobility (Abdullah, Ali, Hussain, Aslam & Javid, 2021). Some insisted that higher mobility leads to higher risk of infection (Zheng, Xu, Wang, Ning & Bi, 2020; Nouvellet, et al., 2021), and this can be partly confirmed by the delay effect of the transit ridership on infection (reflected by effective reproduction number R_t (Zhang, Jia, Wang, et al., 2021)). For this reason, some countries cut down services of public transportation to slow down the spread, which, in turn, would result in lower mobility. In the most extreme scenario, part of the public transit system would close (e.g., metro stations in high-risk zones in China). This instability of services, as well as fear of being infected, discouraged ridership of shared modes of transportation, and thus had a significant impact on people's travel behaviour and sustainable development of the society, since people might turn from public transit to private or active modes (Das, et al., 2021; Kolarova, Eisenmann, Nobis, Winkler & Lenz, 2021).

Overall reduction in human mobility in the pandemic was evident around the globe. Distance and time spent on travel have slumped, and frequencies of trips have shrunk. Statistics Netherlands (CBS) reported that the number of passenger kilometres fell by 60% by train and 24% by car (CBS, 2021a). In the survey made by Beck and Hensher (2020a) in Australia, 78% of respondent households had already made changes to their household travels by mid-April 2020, and the number of household trips per week fell by over 50%. A significant decline in public transit ridership could also be witnessed in Sweden (Jenelius & Cebecauer, 2020) and Hong Kong (Zhang, et al., 2021). Even when the governments gradually restore the economy after the first wave of the pandemic, the travel and daily activities did not come back to normal, especially among the vulnerable groups. For example, a series of surveys carried out prior to, during, and after the first wave of the pandemic by Backer, et al. (2020) in the Netherlands revealed that social distancing policies greatly reduced numbers of physical contacts, where the elderly were the most affected even when the measures were relaxed. However, as many published papers focused only on the first wave of the epidemic to convey the promptest information for policy makers, it is of interest to fully investigate the overall mobility trends over the past two years, which might reflect the change of government measures and public attitudes towards COVID-19 over time.

The restrictive measures have forced people to adjust their **daily outdoor activities** to adapt to the new norm. The impact of COVID-19 varied with the type of the **travel activity**, which could be reflected by the change of (primary) **travel purposes**. In Greece (Baig, et al., 2022), nearly half of the survey respondents stopped their work and recreational activities, and among those who had religious travel (20% of the sample), 85% chose to stop travelling for this purpose. In contrast, four out of five still needed to go out to purchase necessities. In Germany, however, an increase in online purchases led to less frequent shopping behaviour (Kolarova, et al., 2021), which was different from what was observed in Greece mentioned above. Thus, contrary conclusions might be drawn in different geographical contexts, which requires more efforts to investigate and compare.

In this sense, the Netherlands is a special case in Europe of great research value when studying the COVID-19 policies in the first year of the outbreak. On the one hand, the Dutch way of handling the virus in the initial phase of the outbreak was remarkably different from the European counterparts. Neither did the Dutch government order compulsory lockdowns like Germany states, nor did it take almost no coercive measures like Sweden. Instead, the Dutch government implemented so-called "Intelligent Lockdown" including closing unnecessary stores and venues and encouraging teleworking. However, in its second combat against the virus in late 2020, it turned to mandatory lockdown (from 15 December 2020 to April 2021). Therefore, it would be interesting to see to what extent the pandemic situation and governmental policies had affected people's travel behaviour, and how the effects differed with various groups of people.

On the other hand, the research into the impact of COVID-19 on Dutch people's travel patterns is limited, with much focused on the field of public health or public opinion towards COVID-19 countermeasures (Meier, et al., 2020; Chorus, Sandorf & Mouter, 2020) rather than mobility changes. Still, there are some articles focusing on changes of travel behaviour, mainly concentrating on the themes of daily activity patterns (especially for commuting and teleworking) (Ton, et al., 2022) and transport mode choice (public transit, cars, or bikes) (van der Drift, Wismans & Olde Kalter, 2021; Taale, Kalter, Haaijer & Damen, 2022).

This thesis aims to further delve into the major mobility impacts of COVID-19 in the Netherlands, especially on different types of travel purposes. Furthermore, some binomial logistic regression models will be run for each travel purpose to provide insights into the effects of the pandemic and the disparity among different income classes and urbanization levels of residence. In addition, the analysis will be based on the data of Dutch National Travel Survey (*Onderweg in Nederland, ODiN*), which is a large-sample survey (more than 50K respondents) containing abundant information. Governmental large-sample survey as a data source is rare in current COVID-19 – mobility studies, and the thesis is to fill the gap and contribute more understanding to this field in the Dutch context.

1.2. Research aims

Many prior efforts exploring the COVID-19 – mobility interaction focused on decrease of trip frequencies and distance/time travelled or changes in means of transportation. Only some articles analysed changes in primary travel purpose or specific purposes (e.g., commute or shopping). To my knowledge, the research on the Dutch context is still limited. Thus, this thesis tries to fill the gap and focuses on changes of individual travel characteristics by different travel purposes, by presenting data from the Dutch national travel survey of both years (2019 and 2020).

Many researchers tried to model the association between (changes of) mobility behaviour and socio-demographic characteristics in past research. These studies conveyed some valuable information and revealed social disparities behind the findings, but sometimes the patterns varied with regions. It is of my interest to examine such relationship in the Dutch context. **Specifically, this thesis will focus on** whether people's social class (*income group* as an indicator) and residence's spatial setting (*urbanization level* of the home municipality as the indicator) have impacts on the varying **travel decisions** (*whether travelling for a specific purpose or not*) during the COVID-19 pandemic. To investigate whether the influences of these socio-demographic factors depend on the pandemic situation, interaction terms will be added to regression models.

The main research question (aim) of the thesis is – **<u>Did the COVID-19 pandemic significantly influenced people's travel activities and did the impacts varied with income and urban-rural settings of residence?</u>**

Sub-questions of the thesis can then be derived:

1) What was the general trend of individual's travel characteristics (e.g., frequency and distance) per travel purpose during the COVID-19 pandemic in the Netherlands? To what extent did the mobility change from last year?
2) Did the COVID-19 pandemic have significant impacts on people's decisions of travel activities (i.e., travel purposes)?
3) Did the impact vary with people from different income classes or urban-rural settings in the Netherlands? If true, were these effects independent from the COVID-19 pandemic?

1.3. Research framework and thesis structure

The data of this thesis is Dutch National Travel Survey (*Onderweg in Nederland, ODiN*). The first step of the research was to look for early research that dealt with similar data set (i.e., large-sample survey carried out by the government or governmental statistics) and see how they processed and analysed the data. There are more than 350,000 observations and 200 variables in ODiN dataset of these two years, so the next step was to check the variable statistics and clean the data. Finally, after the descriptive statistics and model building were completed, an extensive literature review was made to match the findings with current research.

The structure of the thesis is as followed: Chapter 2 presents literature review on the topics of travel behaviour, social disparity and the impact of pandemics. Details of basic data cleaning and choice of main analytical methods are explained in Chapter 3. Chapter 4 & 5 give descriptive statistics and results of regression models. The last chapter involves discussion and conclusions, where the findings are matched to current studies and practical implications will be provided.

2. Literature Review

2.1. Influencing factors of travel behaviour/patterns and life events/shocks

There is no precise definition of travel behaviour and people usually focus on different aspects of travel behaviour. Some are interested in travel time (Eftekhar, Creemers, & Cools, 2016) or frequency of trips of a specific mode (Nielsen & Haustein, 2019), while some others focused on activity-based travel patterns (such as activity diversity and radius of activity space (Zhang et al, 2021)). Generally, when we try to describe ***travel behaviour*** or ***travel patterns***, it includes a series of indices: travel mode choice, origin and departure time, destination and travel purpose, and aggregated indicators such as total travel distance, time, and frequency.

There are quite a few objective factors that can influence travel behaviour, such as weather (Böcker, Dijst & Prillwitz, 2013), spatio-temporal constraints (Ben-Elia & Ettema, 2011), physical/social capability (Probst, Laditka, Wang & Johnson, 2007; Brough, Freedman & Phillips, 2021), and built environment (Schwanen, Dieleman & Dijst, 2001; Gao, Ettema, Helbich & Kamphuis, 2019), etc. Choice models, which indicate one's preference of a certain choice over the others, usually involving time and monetary costs as predictors, are also used to predict people's travel choice (Gärling & Fujii, 2009).

However, some argue that it is psychological factors that led to fundamental changes in travel behaviour, while the effects imposed by "money" (e.g., monetary incentives or fines) and "power" (e.g., policies or laws) are regarded as temporary (Gärling & Fujii, 2009). This implies that the mobility behaviour was likely to return to normal if, ceteris paribus, the COVID-19 controlling measures lifted. Later surveys carried out around the world proved that this was not the case, as fear of contagion still loomed around us and number of infected cases was still surging. Thus, perception of risk of contagion, a psychological factor, confirmed to be an important factor of travel behaviour during the outbreak of COVID-19 (Borkowski, Jaździewska-Gutta & Szmelter-Jarosz, 2021), leading to aversion to public transportation and avoidance of crowds (Scorrano & Danielis, 2021; Barbieri, et al., 2021).

It is questioned whether the effects of the COVID-19 pandemic on travel patterns are permanent. De Haas, et al. (2020) supposes whether the impact is immediate or structural depends on the longevity and economic consequences of the crisis, while some others supposed that the impact will only last for a couple of years, although some practice like remote working might continue in the future (Bhat, 2020). Many worried that the loss of trust in security and hygiene of public transit mode will exacerbate road congestion and have adverse effects on sustainability (Brough, et al., 2021). But overall, these worries and predictions lack neither theoretical nor empirical evidence so far.

We can explain this issue from two possible perspectives. One is drawn from habit-formation theories. Behaviour is initiated by rational decision making but will become automatic and script-based when repeated in a stable context (Chatterjee & Scheiner, 2015), i.e., habits. When behaviour became habitual, it can prevent an overload on information processing and only require minimal search for external information (Gärling & Fujii, 2009). Habits can also be 'unfrozen' with specific 'incentives' (Fuiji & Kitamura, 2003). If the experience with the alternative travel choice is positive, one will start exploring this new choice. The old habit might finally be abandoned if one keeps receiving positive feedback from the new practice (e.g., switch from bus to driving a car) and the new choice is within their capability (like time and costs).

The other is life course approach. Important life events (shocks) in life course provide 'windows of opportunities' of breaking habitual routines, not only for mobility behaviour, but also daily activity patterns (De Haas, et al., 2020).

The impact of life events or life shocks on travel and activity patterns is well documented in literature. Relocation of residence is one of the most common causes that leads to great changes in commuting travel patterns (Mulder & Hooimeijer, 1999). Change of jobs, car ownership level, and household structure also prove to be associated with commute mode switch (Clark, et al.,2014). De Paepe, et al. (2018) found that holding a driving license or owning a car will encourage car use for all the university/college freshmen surveyed irrespective of residential location, lifestyle, or activity types. Wang, et al. (2020) used China's labour force database and concluded the gender-differential effects of life events, especially childbirth in household, on commuting travel choice of the spouses. Von Behren, et al. (2018) confirmed that an office relocation from the suburb to inner city in Germany change not only employees' commuting mode but also the organization of household tasks, increasing general satisfaction.

The pandemic as a life shock became increasingly visible in academic research since the outbreak of COVID-19. Lu, et al. (2022) gave a survey sample in Xi'an, China where infected cases fluctuated which resulted in *lockdown-unlock policy loop* over the last year. This unpredictability of development of the pandemic was indeed a life shock to the public, significantly increasing commuting travel by e-scooters/ motorbike, taxis and bike-sharing.

According to life course paradigm, a life event may or may not have lasting effects, depending on whether it leads to a **turning point** in the life trajectory. There are three types of life events serving as turning points: life events that open or close opportunities, that make a lasting impact on personal environment, and that change one's self-concept, beliefs, or expectations (Rutter, 1996, in: Chatterjee & Scheiner, 2015). From this perspective, **only when** one's employment or economic status or perception towards public transit and crowds fundamentally change will the impact of COVID-19 be structural and long-term. Thus, this theoretical approach can well explain the nature of the change of travel behaviour.

2.2. Effects of COVID-19 (pandemic) on travel (purposes)

As stated in Chapter 1, a dramatic decline in overall mobility was observed in most countries around the world. As for Europe and Americas, the Netherlands saw an average 55% of decrease in number of trips and 68% reduction in total travelled distance (De Haas, Faber & Hamersma, 2020); frequency of trips made either by subway or on foot fell by more than 90% in Rome during the lockdown while the extent of decrease was only 40% for trucks (Carrese, et al., 2021); New York Subway saw an 90% drop in daily ridership in only one month (Teixeira & Lopes, 2020). As for developing countries, take India as an example, the survey showed that at least 68% people cut down their work-based trips after the outbreak but before the lockdown (Pawar, et al., 2021). There was only one exception in the first wave of outbreak, Tajikistan, where restrictive measures were lenient, few cases were detected, and the impact of pandemic on travel was limited (Yamada & Shimizutani, 2022).

Existing studies covered nearly all stages since the outbreak of COVID-19, with most focused on the first wave in spring 2020. Some article included relaxation period in their research. It was observed that mobility did not return to normal when restrictive measures relaxed in summer, including Australia (Beck & Hensher, 2022), Pakistan (Abdullah, et al., 2021), Italy (Carrese, et al., 2021), which is reasonable as fear of contagion remained.

People generally worried about hygiene, security, and overcrowding (Das, et al., 2021; Politis, et al., 2021) on public transportation, contributing to the sharp decrease in ridership around the globe. The shift from public transit to other modes (private or active modes) were examined in South and East Asia (Das, et al., 2021; Lu, et al., 2022), Italy (Scorrano & Danielis, 2021), Greece (Politis, et al., 2021), and so on. Active modes, i.e., cycling and walking, regained popularity (Song, Zhang, Qin & Ramli, 2022; De Haas, et al., 2020), although Carrese, et al. (2021) monitored a different trend in Rome.

This thesis focuses on changes of people's **travel purposes**. Among all travel purposes, the impact of COVID-19 on commuting travel was the most significant. Essential workers, especially those who needed to combat the virus in the frontline and who had to work under any circumstances to ensure the functioning of cities, such as medical staff, logistics and powerhouse workers, and transit operators (Zubair, Karoonsoontawong & Kanitpong, 2022), had remarkably more trips compared to others (Fatmi, Thirkell & Hossain, 2021). For others, especially those with remote-working capabilities and support from employers, mostly worked from home and had no commuting travel during the pandemic outbreak. Such capabilities and supports were also confirmed to be crucial factors that determined the actual teleworking decision (Brough, et al., 2021; Ton, et al., 2022).

The changes in shopping trips varied with regions. Many countries witnessed an increase in relative share of trips for the purpose of food/essentials purchases, such as Iran (Shaer & Haghshenas, 2021), Australia (first wave (Beck & Hensher, 2020a), and Brazil (Costa, Pitombo & de Souza, 2022). In Pakistan and Thailand, the primary travel purposes switched from work/study to shopping (Abdullah, et al., 2021; Zubair, et al., 2022). Shopping was also an essential travel activity in China (Chen, et al., 2021), though China has one of the most convenient online shopping systems in the world. However, some European and North American countries witnessed a decrease, as online shopping became popular in Germany (Kolarova, et al., 2021), and in Kelowna, Canada picking up online orders became the only one out-of-home activity that saw an increase (Fatmi, et al., 2021).

Leisure trips saw even more variations. An online survey showed that leisure travel became inessential in China (Chen, et al., 2021). The Dutch research by tracing mobile data revealed that making a short walk around the street blocks grew considerably and only saw a decrease when shopping and visiting trips gradually recovered (van der Drift, et al., 2021). Relative share of recreational travel increased in Isfahan, Iran, but the religious and health care travel entirely fell to zero, probably due to local mandatory measures (Shaer & Haghshenas, 2021). Compared to shopping, leisure purpose was less examined in COVID-related studies. Commuting and shopping were of most researchers' interest in literature.

2.3. Social disparity and its impacts on travel response to COVID-19

Social status and spatial setting indicators are of our primary interest in this thesis.

Generally, it is found in current research that the level of decrease in mobility for low-income people was smaller than that of high-income people (Politis, et al., 2021). **Better-educated** people, who usually enjoy the advantages of teleworking capabilities, were more likely to work from home and thus reduce inessential travel (Ton, et al., 2022; Beck & Hensher, 2020a). Similar conclusions could be drawn when linking the **income level** with **geographical** units (e.g., census block groups in the USA (Brough, et al., 2021), census tracts (Coven & Gupta, 2020) or counties (Engle, Stromme & Zhou, 2020)). Chang, et al. (2020) further identified high-risk POIs by simulation where low-income people usually gathered and were more likely to be infected. Additionally, people who were found transit-dependent continually travelled on public transport and their travel patterns were rather inelastic compared to others (Zhou, Liu & Grubesic, 2021).

As for **travel purpose**, the case of King County, USA confirmed that higher-income and better-educated neighbourhoods and individuals witnessed swifter and pronounced mobility change in response to the outbreak of the pandemic (Brough, et al., 2021). Beck and Hensher (2020b) from Australia found in a multi-stage survey that higher-income people reported substantially more trips for both commuting or social/recreational purposes when the measures eased, but they did not state whether the gap between higher- and lower-income group widened or narrowed. In Kelowna, Canada, people with income lower than $50.000 were far more likely to travel outdoor, but the link between the type of activity and income level was not examined (Fatmi, et al., 2021). However, current research concerning variations of travel activities across social demographics is rare. Most simply depicted the changes of frequency of trips of specific travel purposes. Thus, it is of great research value to examine the change in travel activities before and during the COVID-19 pandemic.

There were some contradictory findings in different contexts when referring to work-related travel. While many authors (especially from the United States) asserted that the disadvantaged group still travelled more than higher-income people amid the pandemic, suggesting their need to earn their livings regardless of the shelter-in-place orders, this did not apply to all circumstances. In some countries the unemployment situation caused by the pandemic was severe among low-social-status people. Increasing unemployment would have supressed mobility of low-income groups (Beck & Hensher, 2020b). Another reason could be their fear of contagion on public transportation that they were heavily dependent on. To avoid the risk, they chose to travel less frequently. Thus, the differentiated effects of income on mobility amid the pandemic is uncertain and requires careful investigation.

As for **spatial settings**, this thesis pays special attention to potential disparity in development between urban and rural areas. Some articles did present the impact of pandemic in rural areas. Iyanda, et al. (2022) stressed the disparity in health care between rural and urban regions. The case fatality ratio (CFR) of COVID-19 was higher in rural areas. König and Dreßler (2021) examined the mobility change in a rural district in northern Germany. A modal shift from cars or buses to bicycles was observed. In contrast, the survey done in the more urbanized Germany (63%) found out higher share of "only car" travel in both shopping and commuting trips (Kolarova, et al., 2021). The study in China, though with only a few rural cases in the sample, found that the suspension of public transit systems supressed travel, forcing rural residents to turn to nonmotorized modes. Some families, therefore, probably missed socioeconomic opportunities (Chen, et al. 2021). Though limited, these studies have shown the pandemic had differentiated effects in rural areas. Further investigation is required into the pandemic's effects on different urbanization levels.

2.4. Summary of literature review

This chapter begins with a detailed review of travel behaviour theories and illustrates the impact of life events/shocks on travel patterns. General mobility changes and changes in travel activities are presented next, where we find that changes in work-related and shopping travel were emphasized the most. Lastly, socio-demographic factors that reflect disparity in social status and rural areas are examined. Income is found to be linked with exposure risk and job susceptibility during the COVID-19 pandemic. Rural studies show potential disparity in health and mobility outcomes due to constrained resource, but the impact of urbanization levels is unclear. These findings pave the way for data processing and modelling assumptions in the following chapters.

3. Data and Methods

3.1. Choice of the data set – *ODiN*

To study the mobility trend over time, there are two major sources of data collection: big data from digital devices, and surveys. Digital mobility data generally includes location-based services (LBS) and ridership data, usually with a huge quantity of observations and high temporal resolution. LBS provides real-time locational information that traces changing travel behaviour and activities of individuals on a regular basis which provides convenience for generating O-D maps (Song, et al., 2022). Ridership data of transportation services, involving public transit, shared bike, or ride-hailing services, usually comes from chip-card use, ticket-bundle consumption, or automated passenger counter (APC) sensors (Brough, et al., 2021). As for COVID studies, some also used social media data to study the relationship between outbound mobility of New York residents and social networks (Coven & Gupta, 2020). Digital data is usually objective and avoids self-selection. It usually contains a great amount of longitudinal information and can be linked with individual's socioeconomic demographic (SED) statistics, facilitating analysis of travel behaviour of specific groups of people and comparison over time (Engle, et al., 2020). However, the accuracy of such data sometimes depends on geodata resolution, e.g., estimation based on the size of the basic unit (Kar, et al., 2021). There may be systematic errors leading to biased conclusions if methodology is not well designed.

Another data source – surveying – can be roughly categorized as small-sample and big-sample surveys. With a special focus on COVID-mobility studies, many small-sample surveys started after the outbreak of the pandemic and investigated people's travel behaviour by questionnaires or self-reported travel diaries, among which most were carried out online during strict lockdown periods (e.g., Kolarova, et al., 2021). Since there are people with poor Internet accessibility or low capability of using mobile devices, the samples were usually twisted (e.g., Abdullah, et al., 2021) and the conclusions of such surveys are to be questioned. Besides, many survey questions concerning pre-pandemic travel behaviour were asked in a retrospective way and results might be biased. Respondents might be unwilling to answer questions that would expose their privacy, tended to underreport walking trips that they considered unimportant (Gao, et al., 2020), and might miss out some trips due to poor memory (*also applied for big-sample surveys*). Some other studies asked people's "predictions" of their behaviour after the lockdown. These "expectations" were too subjective and could not be concluded as actual behaviour in the future (De Haas, et al., 2020). These are the disadvantages of most small-sample surveys.

Big-sample surveys, like panel surveys, are usually used for research institutes and the government. Some **panel surveys** starting before the pandemic (De Haas, et al., 2020) were excellent sources of longitudinal analysis at individual or aggregated levels. The design of panel survey can also be flexible, for example, researchers were able to add additional questions regarding the development of COVID-19 (Taale, et al., 2022). In contrast, **governmental surveys** (*official statistics*) were usually based on a much larger population to constitute a representative sample. They were mainly used for statistical reports which released every year.

Dutch National Travel Survey (*Onderweg in Nederland, ODiN*), an extensive survey with more than 40K respondents each year covering observations from nearly every day, is a perfect example. The survey follows a strict framework (sampling – filed work – processing) and the results are reliable. In addition, this survey contains more than 200 variables in total, providing rich information on every aspect of individual's daily travel (CBS, 2022). Big-sample survey data such as ODiN is a rare source in current COVID-mobility studies and is expected to give a comprehensive picture of people's travel behaviour. Therefore, in this thesis, ODiN is used to examine the mobility shift in the first year of the COVID-19 pandemic.

3.2. Data structure and preparation

The Dutch government has carried out several versions of national travel survey since the 1970s, and current version (ODiN) started in 2018. An annual report releases in June every year. In order to have a deeper understanding of the impact of COVID-19 on people's travel behaviour, the yearly survey data of 2019 and 2020 were obtained from an open database DANS (easy.dans.knaw.nl). By running some simple codes in R, we can get a brief summary of data as followed:

Table 3-1. Respondent composition of the data

Year	**Number of respondents***	in which:	…who have made **zero** trip(%)	…who have made **regular** trip(s)(%)*	…who **only** made **other**** types of trips
2019	53380		8230 (15.418 %)	45137 (84.558 %)	13 (0.024%)
2020	62940		16385 (26.033 %)	46551 (73.961 %)	4 (0.006%)

* The number includes people who did not answer some of the questions which caused missing values.

** This includes serial trips, professional truck trips, and professional serial truck trips, as shown in the next paragraph (also in Table 3-2).

Table 3-2. Composition of different types of trips in both years

Year	**Number of people surveyed**	Number of people who made no trip	**Trips that were made**			**Average number of trips per day**	
			…number of regular trips	*…number of serial trips*	*…number of professional truck trips*	*(full sample)*	*(for those who travelled)*
2019	*53380*	8230	150498 (99.33%)	778 (0.51%)	242 (0.16%)	2.84	3.33
2020	*62940*	16385	148133 (99.45%)	606 (0.41%)	210 (0.14%)	2.37	3.18

It is clear from Table 3-1 that 15.4% and 26.0% of respondents **did not make any travel** on the given (surveyed) day in 2019 and 2020, respectively. Considering only the people who travelled, the data separate all trips into four types, namely regular trips, serial trips, professional truck trips, and professional serial truck trips (the latter two were merged in Table 3-2). According to CBS (2020), "**serial trip**" stands for "a series of successive work-related trips that are included in the file as a whole". Though it did not clearly distinguish the difference between **regular trips** and serial trips, at least we can understand "serial trip" as work-related trips and these trips were "*not part of daily mobility*" of individuals (CBS, 2020). Moreover, only a very small proportion of trips were serial or professional truck trips (less than 0.7%) and an even smaller percentage of people (less than 0.1%) made only serial/professional truck trips. This means considering only regular trips would not affect the research conclusion to a large extent and is therefore acceptable. **Therefore, only regular trips will be included in the final samples**.

The survey questionnaire mainly consists of four parts. (1) Opening: checking personal information, the entry date and associated (surveyed) date. (2) Location: time, addresses, and activities. (3) Journeys: tables with transportation modes, and time and distances. A specific focus on car and train trips. (4) Ownership: ownership of e-bikes and cars, average use of means, and questions of social status and education (CBS, 2020). The data contains answers to all these questions and is structured hierarchically as Fig. 3-1 shows, in which trip and trip legs were stored under the same individual ID (*OPID*) and thus each respondent may have one or more observations (rows) in the file.

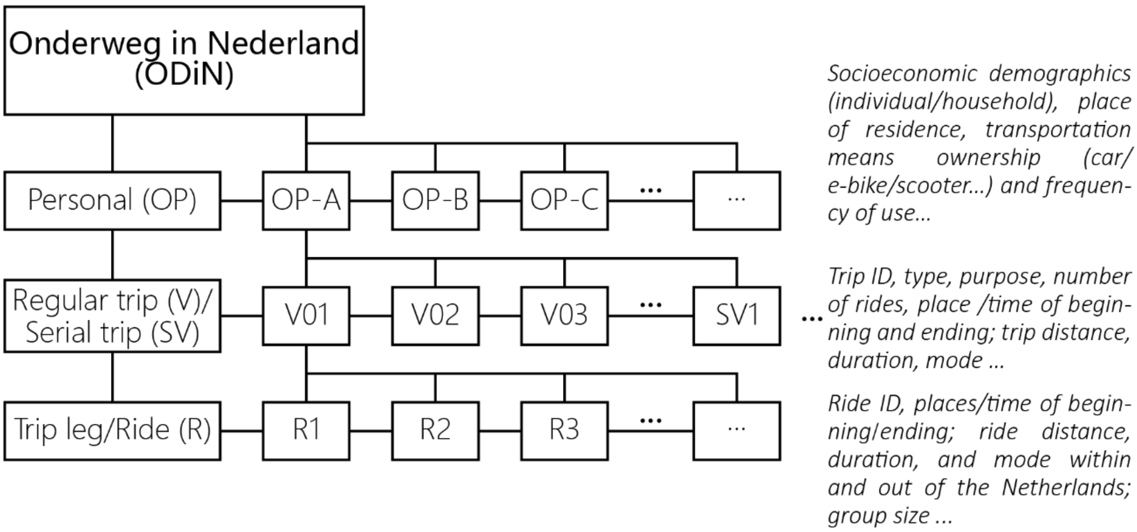

Fig. 3-1. Overview of ODiN data structure.

By comparing the codebook and data, all 208 variables were checked. Observations with **missing values** in socio-demographic attributes were removed in the analysis. Thus, 44260 and 45534 people each year remained in the data for daily regular travels.

Table 3-3. Number of respondents in each sample after screening

	Sample A: ***only*** include people who made ***regular*** trips	**Sample B:** include people made ***no trips*** or ***regular*** daily travel	Total number of *regular trips* made
2019	37742	44959	126348
2020	39537	53500	127046
Sum	77279	98459	/

As many current studies only investigate adults in the survey, minor respondents (aged under 18) are removed from the final data to make comparisons convenient.

After these screening processes, the number of respondents and definition of each sample are shown in Table 3-3.

3.3. Development of the pandemic

The SARS-CoV-2 virus was first confirmed in Wuhan, China after several pneumonia cases for unknown cause were reported in December 2019. In January, the virus later spread to Europe. In March, full-scale outbreak in Europe, then the Americas and worldwide. COVID-19 was finally declared as pandemic by WHO. As of October 2022, more than 600 million cases were confirmed around the world, and 6.5 million people had died from the disease.

Table 3-4. Number of respondents in each sample after screening

Months of 2020	**Month groups**	**Reasons for divisions**	Important COVID-19 policy changes (Timeline) (Coronavirus Dashboard, 2022)
January	**A**	Pre-pandemic	24/1: Installation of Outbreak Management Team
February			**27/2: First case emerged** (North-Brabant). Start of Phase-1 control.
March	**B**	The beginning of the outbreak **since March**, and *Intelligent Lockdown* took effect in **mid-March**. ***– March as a transition month.***	9/3: Hygiene measures. (WFH request for North-Brabant) ***12/3: Start of Phase-2 control – Intelligent Lockdown***. All events including theatres, sports clubs and museum were forbidden. Request to work from home. **15/3: Closure** of the catering industry, sports facilities and schools. 16/3 & 20/3: Speech of PM and King. **23/3:** All events are forbidden, specifically, **services in which contact cannot be avoided** (e.g., *hairdressers*) 25/3: Protocol responsible shopping.
April	**C**		
May		Measures start to relax since mid-May, but the willingness of outing was still low.	**11/5:** Opening of elementary schools on a 50% basis. Stops of stay-home orders, except people with symptoms. **Services in which contact cannot be avoided are allowed to open and outdoor sport activities are allowed** (following the 1.5-meter-social-distance procedures as much as possible)
June	**D**	**It was not until June** that a **significant rebound** of human travel was witnessed.	**1/6: Opening of restaurants, movie theatres and museums with limitation.** Public transport operates in normal mode (mouth masks obliged). 2/6 & 8/6: Complete opening of secondary and elementary schools. 15/6: Nursing homes are allowed to welcome visitors. Visiting countries in Europe is permitted and vice versa.
July		Traditional holiday seasons in summer.	**1/7: Further lifting of restrictions regarding gatherings.** Camping sites and holiday parks were allowed to open (with social distancing),
August		Beginning of work for students and people back from holidays. **Since mid-**	**18/8: New restrictions of a maximum of 6 people allowed for visiting.**
September	**E**		29/9: Maximum of 3 people visiting. Pubs and restaurants must close earlier.

		August, the measures became stricter again. ***– September as a transition month.***	
October		Beginning of (partial/full) lockdown.	**14/10: *Partial Lockdown*. Restaurants and cafes closed. No events permitted.** Urgent advice to wear a face mask in indoor public areas.
November	**F**	The measures were gradually tightened	4/11: Reinforcement of partial lockdown. Max. 2 ppl visiting. Most publicly accessible locations closed, except hotels, gyms, airports, etc.
December			**15/12: Lockdown.** People working in contact-based industries cannot perform their work. All publicly accessible venues closed.
Jan 2021	Not applied (2021)		6/1: Beginning of the vaccination program. 23/1: Curfew orders took effect. 26/1: Rise of *Alpha* variant was witnessed by RIVM.

The Netherlands confirmed its first case on 27 February, after the pandemic outbreak in neighbouring EU countries. The cases rose dramatically, and in March 12, Dutch cabinet introduced "Intelligent Lockdown". The term means that not all shops were closed, supermarkets remained open, and people were still allowed to go outdoors (CBS News, 2020). With collaboration with Dutch citizens, the intelligent lockdown worked, and infected cases went down steadily since late April. The business and education gradually reopened in May, and fully open in June. But as the cases grew again, Dutch government started to limit the number of visits since August, and finally ordered partial lockdown in October (and full lockdown in December). The timeline of policies is shown in Table 3-4.

Overall, it can be concluded that there were **two waves of large-scale infection** in 2020. By going through the concrete dates of policies, we roughly divide year 2020 into **six phases** following the development of COVID-19, including a pre-pandemic phase (Jan – Feb), two waves of outbreak (Apr-May & Oct-Dec), a relaxation phase (Jun – Aug), and two **transition months** – March and September, when policies became stricter than previous phase but not all people adapted to the changing situation.

Month groups are ***recorded*** in next few chapters following this simple rule: *"MA-2020"* represents month group A (Jan – Feb) in 2020, and a simple *"MC"* represent the month group C (Apr – May) generally (with the year not given).

Grouping months help us model the effects of the pandemic on mobility more specifically.

3.4. Analytical methods

The thesis is to study the change of travel patterns in each travel purpose (representing a type of travel activity) during the COVID-19 pandemic. In next chapter, socio-economic demographic characteristics of respondents (from sample B) will be examined in first place. Later, graphs and tables will be made to describe the general changes in distance, time travelled and number of people who made trips (probability of travel) of each travel purpose between two years. Difference among income groups and urban-rural settings will also be compared by the same method. Hypothesis for modelling can be drawn from these plots and data.

After descriptive analysis, four binary regression models will be derived for all travel purposes to study the correlation between probability of travelling (defined in section 4.3) for the given purpose (work, leisure, shopping and visiting) and interested variables. Months are divided in groups according to the stages of the pandemic in the Netherlands in 2020 (Table 3-4) so as to reduce potential contingency caused by small number of respondents in some months. These month groups act as core independent variables to indicate the effects of both the pandemic and relevant governmental measures. Urbanization classes and income groups, as primary variables of interest to indicate potential disparity in social status and urban-rural development, are also included in the basic models. Other socio-economic demographic attributes will act as controlling variables in the models.

Based on the results of basic models, interaction terms between month groups and independent variables reflecting social-status/spatial-setting features which are significantly correlated with the travel probability in the basic models will be added to the original regression models in the last part of analysis. This is to study whether those socioeconomic factors rely on the effects of the pandemic. Discussion will be made based on these model results.

4. Descriptive statistics

4.1. Sample demographics

Table 4-1 presents descriptive statistics of the complete sample (B) that includes both people who made regular travels and who did not travel on the surveyed day[1]. Most people aged 45-59 years old. More than half of the sample lived in West Nederland, the economic engine and the most densely populated part of the nation. Most people have an automobile driving license, and more than 30% of people have at least two cars in their households.

High-income people are overrepresented in the sample (each class should be around 20% in normal situations). Besides, compared to Dutch population (see *de Haas, et al. 2020; van der Drift, et al. 2021*), young people (below 30) were slightly underrepresented in contrast to the overrepresented old (above 65). As for ethnicity and education attainment, people with Dutch background[2] and high level of education also saw a small overrepresentation. Two-person household also witnessed a higher proportion than that of population (35.7%). However, the survey sample is still a fair representation of total population, except an overrepresentation of high-income people which may lead to bias in the results.

Table 4-1. Socioeconomic and demographic characteristics of Sample B

	2019 (ref.)	2020
Standardized disposable income (from low to high)		
First 20%	5674 (12.62%)	7058 (13.19%)
Second 20%	7909 (17.59%)	9411 (17.59%)
Third 20% (Mid)	8421 (18.73%)	9829 (18.37%)
Fourth 20%	10364 (23.05%)	12183 (22.77%)
Top 20%	12591 (28.01%)	15019 (28.07%)
Urbanization class of the home municipality (Average Area Address Density per km2)		
1.Most strongly urbanized (≥2500)	12558 (27.93%)	15547 (29.06%)
2.Highly urbanized (1500~2500)	13348 (29.69%)	16170 (30.22%)
3.Moderately urbanized (1000~1500)	7086 (15.76%)	8397 (15.70%)
4.Little urbanized (<1000)	11967 (26.62%)	13386 (25.02%)
Month group (ID)		
Jan-Feb (A)	7587 (16.88%)	8688 (16.24%)
Mar (B)	3839 (8.54%)	4302 (8.04%)
Apr-May (C)	6856 (15.25%)	10359 (19.36%)
Jun-Aug (D)	10588 (23.55%)	12811 (23.95%)
Sep (E)	3756 (8.35%)	4197 (7.84%)
Oct-Dec (F)	12333 (27.43%)	13143 (24.57%)
Age		

[1] The descriptive statistics of Sample A are similar to that of Sample B. Only the Sample B's table is provided here. For the descriptive statistics of Sample A, see Appendix A.

[2] About national origins of migration, see Wikipedia https://en.wikipedia.org/wiki/Demography_of_the_Netherlands, or table information ⓘ of https://opendata.cbs.nl/statline/#/CBS/en/dataset/37325eng/table?ts=1662269626113.

18~29	7537 (16.76%)	9375 (17.52%)
30~44	9845 (21.90%)	11907 (22.25%)
45~59	12040 (26.78%)	13666 (25.54%)
60~74	7230 (16.08%)	8358 (15.62%)
>= 75	8307 (18.48%)	10194 (19.05%)
Gender		
Female	21872 (48.65%)	26762 (50.02%)
Male	23087 (51.35%)	26738 (49.98%)
Ethnicity (Immigration background)		
Dutch	35708 (79.42%)	41222 (77.05%)
Western background	4471 (9.94%)	5683 (10.62%)
Non-western background	4780 (10.63%)	6595 (12.33%)
Social participation		
Part-time workers (12-30 hours per week)	6296 (14.00%)	7459 (13.94%)
Full-time workers (at least 30 hours per week)	18552 (41.26%)	21846 (40.83%)
Students	3092 (6.88%)	3815 (7.13%)
Retired/VUT	10295 (22.90%)	12476 (23.32%)
Unemployed & incapacitated	2200 (4.89%)	2697 (5.04%)
Own household and others	4524 (10.06%)	5207 (9.73%)
Education attainment		
No or primary education	2310 (5.14%)	2598 (4.86%)
Lower vocational education	8316 (18.50%	9325 (17.43%)
Secondary vocational education	14499 (32.25%)	16681 (31.18%)
Higher vocational education & university	18502 (41.15%)	23047 (43.08%)
Other training	1332 (2.96%)	1849 (3.46%)
Number of household members		
1	8732 (19.42%)	10770 (20.13%)
2	18629 (41.44%)	21897 (40.93%)
3	6685 (14.87%)	7812 (14.60%)
4	7689 (17.10%)	9216 (17.22%)
>=5	3224 (7.17%)	3805 (7.11%)
Household composition		
Couple with children	16321 (36.30%)	19300 (36.07%)
Couple without children	17354 (38.60%)	20440 (38.21%)
Single-parent household (with children)	2322 (5.16%)	2687 (5.02%)
Single-person household and others	8962 (19.93%)	11073 (20.70%)
Household car ownership		
0	7106 (15.81%)	8950 (16.73%)
1	22300 (49.60%)	26117 (48.82%)
2	12014 (26.72%)	14285 (26.70%)
>=3	3539 (7.87%)	4148 (7.75%)
Respondent holding a driving license		
Yes	38304 (85.20%)	45104 (84.31%)
No	6655 (14.80%)	8396 (15.69%)
Weekday		
Sunday	15.02%	14.85%

Monday	14.40%	14.18%
Tuesday	14.42%	14.24%
Wednesday	13.86%	13.81%
Thursday	13.94%	14.18%
Friday	14.27%	14.29%
Saturday	14.09%	14.45%
Bank holiday		
Yes	980 (2.18%)	1473 (2.75%)
No	43979 (97.82%)	52027 (97.25%)
Region* of residence		
North Netherlands	3846 (8.55%)	4106 (7.67%)
East Netherlands	8794 (19.56%)	9286 (17.36%)
West Netherlands	23818 (52.98%)	30129 (56.32%)
South Netherlands	8501 (18.91%)	9979 (18.65%)

* For statistical purpose, the Netherlands is divided into four regions, namely North, East, West, and South Netherlands. Each region includes these following provinces:
North - Groningen, Friesland, and Drenthe; East - Overijssel, Flevoland, and Gelderland;
South - North-Brabant, and Limburg; West – North-Holland, South-Holland, Utrecht, Zeeland.

4.2. General mobility change, travel purposes, and reasons for not travelling

The general changes of total travel distance, time, and frequency per person per day between 2019 and 2020 were impressive (Table 4-2). Both samples saw great loss in both average and median values of travel distance. Average travel time and average number of day trips also reduced noticeably (especially in the complete sample (B)). The decline was so great that the impact of the pandemic could not be ruled out.

Share distribution of travel purposes implies the shift of main travel activities. To make it easy for analysis, all travel purposes mentioned in the original data were merged into 6 classes: **work** (commute and professional), **services/care**, **shopping**, **leisure**, **visit/stay**, and **others**. As shown in Table 4-3, *among all regular trips*, the *relative* proportion of work-related trips fell by 6.70% while shopping trips saw a 4.38% increase. The relative share of recreational trips slightly grew. Percentage of trips for services/care and visit/stay decreased a little bit. These relative changes prove that among all activities shopping and working trips changed the most, but in opposite directions.

The changes in travel purposes can also be depicted by the *absolute* share of *the person's sample*, generated by dividing number of people engaging in travelling for a given purpose by the number of respondents in the sample (B). It could be found from Table 4-4 that the working and visiting trips descent greatly, while share of leisure and shopping trips kept largely stable. Since people may have more than one regular trip per day, the sum of the absolute percentages surpassed 100%. A 16.5 percent difference of sum of percentages was found in 2020, which indicates a strong decline in overall human mobility and diversity of activities per person per day. This reduction existed in **all** travel purposes, reflecting an overall shrinkage of outdoor activities in the COVID-19 era.

Section 3.2 reveals that the number of people who did not make any trips almost doubled in 2020 (share increased from 15.4% to 26.0%), so the reasons of being inactive would be of interest to investigate. Table 4-5 presents the number and share of people giving different reasons for their not travelling in both years. Share of work-from-home almost tripled, and "other reasons" also saw an approximate 10% increase (the detailed explanation of 'other' is unavailable). As expected,

Table 4-2. Descriptive statistics of total distance, time, and number of trips travelled per person per day (p.p.p.d.)

	2019		2020	
(Sample B)	Mean (SD)	Median	Mean (SD)	Median
Total distance travelled per person per day (p.p.p.d.) (km)	40.89 (60.04)	17.9	26.27 (46.74)	8.4
Total time travelled p.p.p.d. (min)	80.13 (78.19)	60	63.28 (71.79)	63.3
Total number of trips p.p.p.d.	2.81 (2.08)	2	2.37 (2.15)	2
(Sample A: for those who have travelled)				
Total distance travelled p.p.p.d.	48.71 (62.56)	24.8	35.54 (51.24)	16
Total time travelled p.p.p.d.	95.45 (76.29)	75	85.63 (71.13)	67
Total number of trips p.p.p.d.	3.35 (1.84)	3	3.21 (1.88)	3

Table 4-3. Share of daily travel purposes among all regular trips (Sample A)

Origi-nal code	Original motive category	Merged motives	**New code**	freq.2019	2019/%	freq.2020	2020/%
1	To and from work	Commute & Professional (work-related)	1	35823	**28.35%**	27506	**21.65%**
2	Business and Professional						
5	Follow education/course						
3	Services/Personal Care	Services/ Personal Care	2	4472	**3.54%**	4236	**3.33%**
4	Shopping/groceries shopping	Shopping	3	27651	**21.88%**	33364	**26.26%**
7	Social recreational other	Leisure	4	30854	**24.42%**	32973	**25.95%**
8	Touring/hiking						
6	Visit/stay	Visit/Stay	5	12726	**10.07%**	12216	**9.62%**
9	Other motive	Others	6	14822	**11.73%**	16751	**13.18%**
				126348		127046	

Table 4-4. Absolute share of people travelling for each purpose in 2019 and 2020 (Sample B)

Travel purpose	2019 (*ref.*)	2020
Work	17179 (38.21%)	13313 (24.88%)
Leisure	16284 (36.22%)	19258 (36.00%)
Shopping	12715 (28.28%)	15000 (28.04%)
Visit	6862 (15.26%)	6585 (12.31%)
Sum of percentages	***117.97%***	***101.23%***

relative proportion of "staying abroad" reduced the most[3], since people avoided long tours (whether for business or relaxation) and the border control was strict during the pandemic. Share of "no outdoor activities", however, saw an unexpected decrease. Maybe it was partly "substituted" by work-from-home.

Though the questionnaires were not specially designed for the COVID-19 situation, some interesting findings were found, and the observed mobility trend partially correspond with that in literature (Zubair, et al., 2022; Beck & Hensher, 2020a). By these four simple tables, we can already see the mobility decline and increase of remote working between these two years.

Table 4-5. Reasons of not travelling in both years

VAR.	Explanation	2019		2020	
1	Illness and/or injury	603	8.36%	917	6.57%
2	Physical limitations and/or disability	539	7.47%	763	5.46%
3	Weather conditions	474	6.57%	770	5.51%
4	**Work from home/profession at home**	330	**4.57%**	1580	**11.32%**
5	Study at home	167	2.31%	518	3.71%
6	Taking care of family members	369	5.11%	492	3.52%
7	**No outdoor activities**	3078	**42.65%**	5159	**36.95%**
8	Transport was too expensive	37	0.51%	38	0.27%
9	No suitable transport available	48	0.67%	61	0.44%
10	**Stay abroad**	529	**7.33%**	324	**2.32%**
11	**Other reasons**	1043	**14.45%**	3341	**23.93%**
		7217		13963	

4.3. Change of travel distance, time, and probability per travel purpose

To gain a deeper insight into the change of different travel activities, three indices were calculated from the original data set for analysis: travel distance, travel time (duration), and travel probability. The definitions are as follows.

(1) **Travel probability**: The ratio of the number of people travelled for the given purpose X on the surveyed day to the total number of respondents (sample B) is defined as ***the probability of travelling for purpose X*** (shortened as ***travel probability*** of X in following sections). The probability is calculated per group. Groups are divided according to years, month groups, or urbanization levels, etc.

(2) **Travel distance/time**: the total distance travelled / time spent by the respondent *for the given travel purpose* on the surveyed day. Since *only a small fraction* of people will do the given travel activity on the surveyed day as Table 4-3 shows, there must be excess number of zeros (representing people

[3] The ODiN survey data only analyse the travel distance, time, and frequency within the border of the Netherlands and record foreign trips separately. Therefore, total distance of zero only means the respondent does not travel in the Netherlands, but whether he makes trips in any foreign countries is unknown. The figure implied that the reduction of foreign travel did not transfer to domestic travel, suggesting that the travel demand was supressed during the pandemic.

who do not travel for purpose X on the surveyed day but may do such activity on other days) which would cause difficulty for analysing the difference among these motives. So, Sample A is used for calculating mean total travel distance/time in following sections to reduce the effects of excess zeros[4].

The following sections will show the changes by month groups per travel purpose. Four travel purposes are to be studied: **work, leisure, shopping, and visit/stay**.

4.3.1. General changes

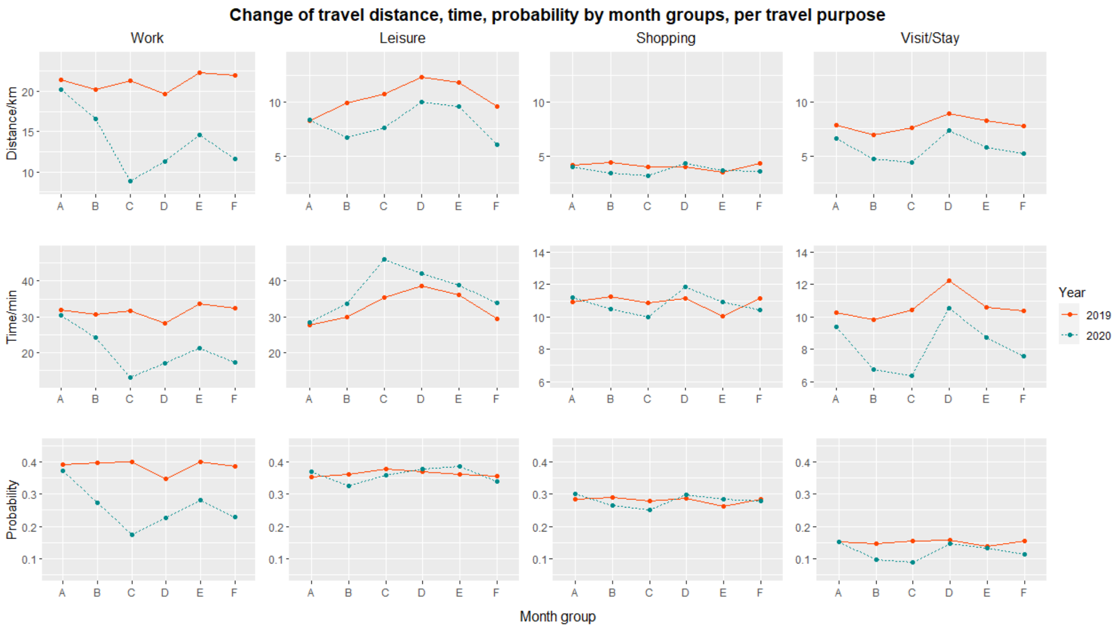

Fig. 4-1. Changes of travel distance/time/probability per purpose between 2019 and 2020.

Generally, the change of work-related travel between 2019 and 2020 was the most remarkable of all travel purposes in all three indices we studied in this section (Fig. 4-1). Meanwhile, shopping was the least impacted travel activity (see also: Appendix B.1).

The travel probability for leisure and shopping purposes remained almost the same in 2020 when compared to last year. In contrast, work travel probability dropped dramatically since the outbreak of COVID-19, from around 40% down to an average of 23%. The lowest point of working travel was in MC-2020 (April – May) amid the most serious time of the pandemic, despite the partial relaxation of measures since 11 May. During this period, the work travel probability saw a 56% of decline, and both average travel distance and time fell to only 42% of previous year. Visit travel also experienced a 40% descent during this month group, though it was already the least frequent activity pre-pandemic.

The shopping travel had the most stable pattern: the distance and time travelled did not change much through both years (especially in the pre-pandemic 2019).

[4] Sample A is used to show the opposite directions of changes of average distance and time travelled for leisure purpose. If it is to reveal the general impact of the pandemic on mobility, Sample B is better.

The summertime is believed to be a typical holiday season as both a low point of working travel and high point of recreational (and/or visiting) travel can be seen in graphs.

It is interesting to find a strong increase in total time travelled for leisure after the outbreak, while its total travel distance changed in an opposite direction. Thus, it can be inferred that people had more recreational trips around their neighbourhood blocks instead of farther places during the spring lockdown.

4.3.2. Variations with income groups

Respondents are divided into three income groups according to the standardized disposable income –

(1) Low-income group, comprising the lowest three deciles.

(2) Middle-income group, formed by people from the 4th to 7th decile of standardized income.

(3) High-income group, whose income belonged to top 30% of the population.

This section is to analyse potential variance of travel patterns (described by three given indices) with different levels of income.

The difference of work travel distance, time, and probability among three income groups were remarkable, and their changes with months followed clear patterns (Fig. 4-2). On average, high-income people travelled more distances and spent more time on work travel than middle-income people, and the middle-income travelled more than the low-income. The probability of work travel also differed greatly between groups, with high-income people 20% more likely (see Appendix B.2) to travel for work than the low-income pre-pandemic. Generally, a low point in summer and a high point in September can be found on curves.

After the outbreak of COVID-19 in March 2020, a significant decline of work travel distance, time, and probability could be witnessed among all income classes, and the gaps between groups had been narrowed. The curves hit the lowest points in MC-2020 instead of summer. Interestingly, the decline of low-income people was even stronger than high-income people, which contradicts existing research (Brough, et al., 2021). This could be contributed to the closure of contact-based sector that were usually occupied by people of low social status. In this sense, low-income people could suffer more and might even become unemployed in the pandemic compared to high-income people who could choose to work remotely. However, the 20% of work travel probability of high-income group in the most severe period of the pandemic still cannot be well explained.

The work travel patterns did not turn back to normal when measures relaxed in summer, and the curves went down again in the last quarter: in MF-2020, only 25% of high- and middle-income respondents travelled for work on surveyed days, and the share was even lower for low-income people (17%).

Another daily activity that was hit strongly by the pandemic and related policies should be visit/stay. This is reasonable as Dutch governments started to set the maximum number of people allowed for home-visit in August and gradually strengthened the limitation in following months (from 6 to 2). The general trends of visit travel in both years were clear, with the curves being rather flat in 2019, and a sharp decrease in MB-2020 as well as a strong rebound in summer of 2020. However, the difference among income groups cannot be distinguished, so income might not be a significant influencing factor. The gap between income groups was larger at some time points, which might reveal discrepancy in perception of risk of infection.

The leisure travel probability and travel time stopped decreasing and climbed up again in MC-2020, showing a sharp contrast with work or visit travel. The difference of time/distance among income groups between both years became smaller, while the gap of travel probability became even widened, with high-income group enjoying a higher probability to travel for recreational purpose.

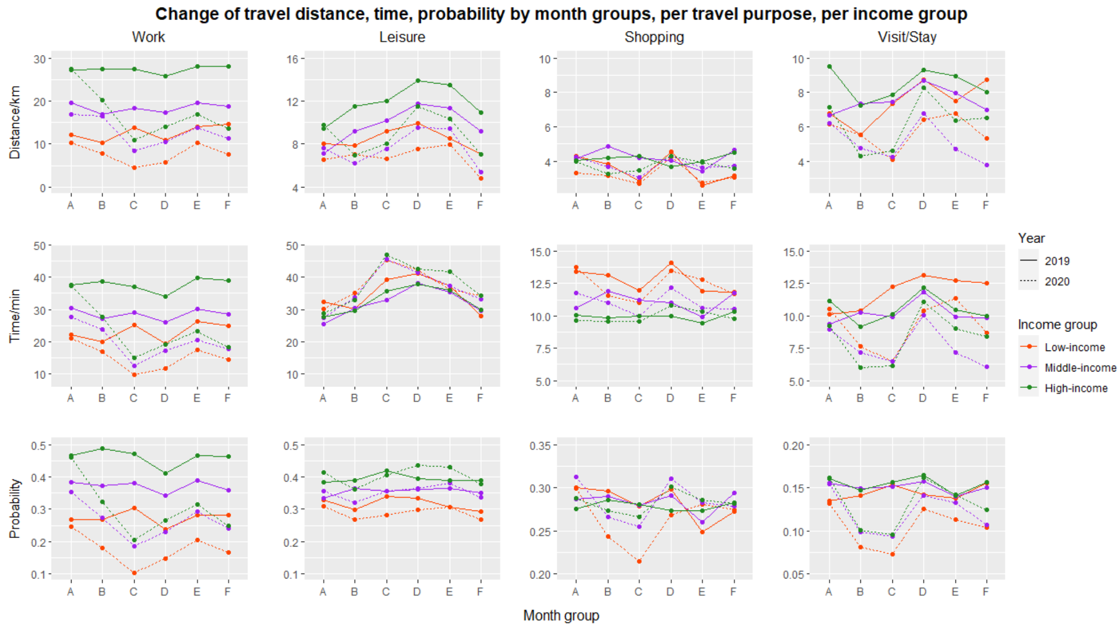

Fig. 4-2. Changes of travel distance/time/probability per purpose ***per income group*** between two years.

In the most dangerous period of the initial outbreak in April and May, time spent on leisure travel showed an extraordinary increase (40% more than last year and 30% more than previous month-group) and the travel probability also appeared to grow steadily when the mean travel distance remained low. However, different responses were made by Dutch people in terms of leisure travel in the second wave of the pandemic. The recreational travel time saw a steady decline since June, and all three indices slumped in MF-2020 compared to summer. The travel distance dropped to 4.8km and 7.1km for low- and high-income group, respectively, a loss greater than 30% compared to the previous year. Yet, the travel probability did not decrease much, and the travel time (about 35 min/d[5]) was even longer than that in

[5] In section 4.3, all calculation and comparison of travel distance and travel time between groups are based on Sample A. Different findings might be drawn if the calculation was based on Sample B, since the excess zeros could lead to declining patterns in all income/urbanity classes across all travel purposes.

2019.

The shopping patterns were the hardest to interpret. The extent of change of shopping travel time and probability were rather low when compared with other travel purposes. The patterns of shopping travel distance were too fluctuating to explain. Specifically, when comparing low-income group with other income groups, they always spent much longer time on the way to shopping, although their travel distance was even more fluctuating over time. The travel probability for shopping hit a low point in MC-2020 on the graph, but the gaps between groups were only 5%, much narrower than that in work and leisure travel.

Overall, the most common travel activity, working, had the clearest pattern and sharpest decline in all three indices across all travel purposes studied in the thesis. The patterns of other three activities were less clear, but some findings also revealed potential income disparity. For example, low-income people had to spend much more time getting to the shopping place even in the pandemic, and their shopping locations dispersed spatially which might contribute to huge fluctuations in travel distance throughout the years. Additionally, low-income people also spent less time for leisure trips, and their jobs probably suffered a lot amid the pandemic. These phenomena provide implications for policy makers as well as hypotheses for regression models.

4.3.3. Variation with urbanization levels of home municipality

Urbanity level, or urbanization class, is defined as the neighbourhood address density of the municipality in question. The address density is determined with a radius of 1km around that address. A density value is derived for each municipality by calculating the average address density for all addresses within that municipality (CBS, 2020). Thus, the urbanity level in the data was depended on the municipality where the respondent lived (registered). All 355 Dutch municipalities were reclassified into four urbanization classes to describe the urban-rural continuum as shown in Table 4-1:

Level 1 (U1). Most strongly urbanized (≥2500 addresses per km^2).

Level 2 (U2). Highly urbanized (1500~2500).

Level 3 (U3). Moderately urbanized (1000~1500).

Level 4 (U4). Little urbanized (<1000).

The number of municipalities belonging to each level is counted in Appendix C. The number of respondents and percentage of each class was shown in Table 4-1. Apparently, more than half of the Sample B live in highly urbanized areas (Level 1 & 2) in the Netherlands.

Patterns for these urbanity levels appeared to have something in common with those for income groups, but the difference between urbanity levels seemed to be much smaller (Fig.4-3). Nevertheless, some interesting findings could be drawn.

As for travel probability, the shopping travel patterns for people in cities of different urbanization levels seemed fluctuating from the graph, especially after the outbreak. However, the gaps between each level were much narrower than that between income groups. Generally, the only regularity we can capture is that the probability hit a low point in MC-2020 and saw a temporary rebound in MD-2020.

Similarly, the average leisure travel probability did not change much across the year 2019 for all urbanization classes. Similar fluctuation existed in 2020: all groups hit a temporary low point in March at the beginning of the outbreak, but 'immediately' showed a strong rebound in MC-2020 (Apr – May). The most urbanized residents were the most impacted, but their lowest leisure travel probability in 2020 was still above 25%. It could be asserted that leisure travel probability did not suffer seriously and stayed largely stable. Overall, it is difficult to interpret the changing pattern of travel probability for both leisure and shopping purposes.

For visiting, the least common travel activity, its average travel probability was only 9% in MC-2020, 6 percent lower than last year. The recovering speed varied – in MD-2020, the probability for the most urbanized residents to pay a visit was almost the same as last summer, but for the least urbanized residents the difference was 2% less than 2019. Winter was popular time for Christmas and New Year's family visits, and in 2019 the probability (Oct-Dec) was higher than the previous (ME) for residents from all urbanity levels, while in 2020 the probability became lower than ME, partly attributed to the government measures setting the cap for visiting in the second wave.

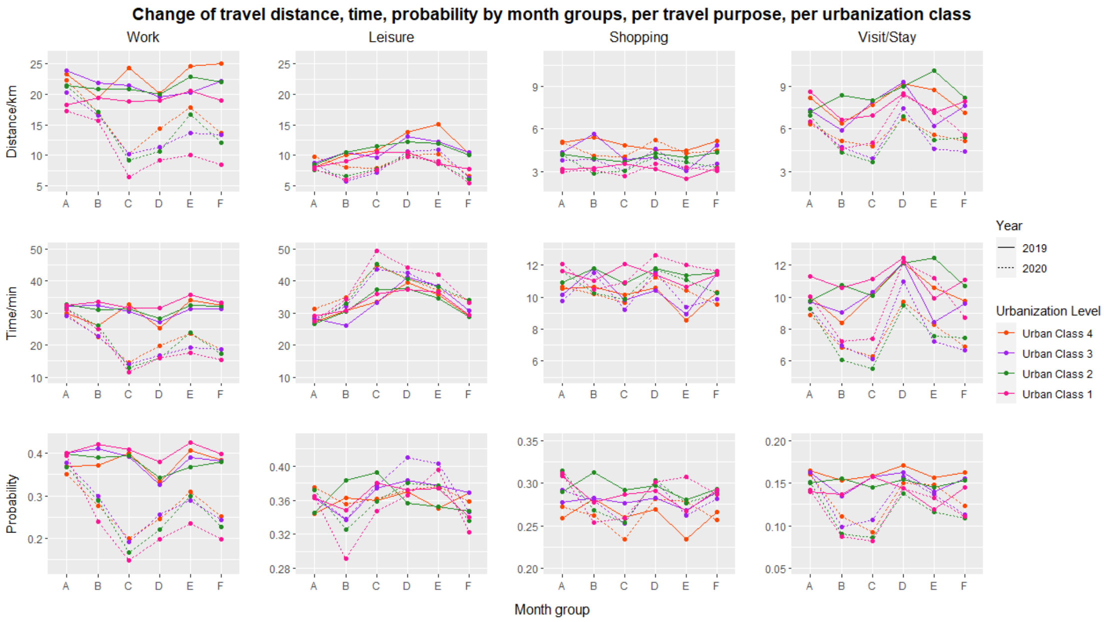

Fig. 4-3. Changes of travel distance/time/probability per purpose ***per urbanity level*** between two years.

Work travel probability in 2020 was a sharp contrast to that in 2019. Respondents living in the most urbanized cities were on average 48% less likely to travel for work after the outbreak, becoming the most probable to stay home among all groups. The probability dropped by 33% on average for people living in the less urbanized areas (Level 2-4) compared to 2019. But before the pandemic, the most urbanized residents were the most likely to go out for work than residents from all other urbanity levels. The gaps between urbanity levels were also smaller than that between income classes.

When it refers to people who made regular travel on the surveyed day (**Sample A**), respondents living in the most urbanized cities travelled fewer distances but spent more time for work travel than any other urbanization classes in normal time. In 2020, they turned out to have the shortest average travel time spent on commute and profession, though the difference between classes did not change much when comparing data of both years.

Changing patterns of travel distance and time for other purposes of all urbanity levels shared many similarities with that of income groups, but the curves saw more fluctuations and the patterns were vaguer. Generally, the changing patterns were the same as Section 4.3.1. Specifically,

- Visit travel
    - The travel distance and time were at their lowest points in the first wave from March to May.
    - The travel time almost returned to normal in MD-2020, while there was still a 20% gap for travel distance between two years.
    - Of all the groups, the most urbanized areas' residents recovered the best. In summer, their visit travel distance and time was almost the same as 2019, even surpassing data of 2019 in September.
- Shopping travel
    - No clear patterns can be concluded for shopping travel, but generally the most rural residents spent more time and travelled longer distance to shops and malls than the most urbanized residents, regardless of the impact of the pandemic.
- Leisure travel
    - The average travel distance of respondents from the most rural part of the nation was longer than those from the most urbanized areas before the pandemic. However, this relationship did not exist in 2020. There was no such pattern in leisure travel time, either.
    - Biggest increase for average travel time in MC-2020 for people from all urban-rural settings. The travel time was longer in MF-2020 (2^{nd} wave) than last year, but shorter than that in the first wave.
    - Leisure travel distance saw similar levels of decrease in both waves compared to the same period of last year, reduction by around 30-40%.

4.3.4. Conclusion of descriptive analysis

By plotting the changing patterns of travel probability, travel distance and travel time for each travel purpose, it is obvious that work travel had the clearest pattern and was the most negatively impacted. Changes in shopping travel over time were the smallest. Visit travel was the activity least taken place, but it was also negatively affected. The most interesting part is that leisure travel witnessed increase in time spent but decrease in distance travelled (sample A). Patterns showed remarkable difference between income and urbanization classes in the case of work travel, but this **did not apply** for other travel purposes. Therefore, following hypotheses are made for regression analysis:

1) Significant effects of the pandemic, income classes and urbanity levels on work travel can be found, with perfect goodness of fit.
2) Month groups will have significant effects on leisure, shopping, and visiting travel, but income and urbanity may not. The goodness of fit of these models might be low.
3) The impact of socio-demographic factors (esp. income and urbanity) on leisure, shopping, and visiting travel might not depend on the effects of the pandemic, but things would be different for work travel.

Several **binary logistic regression** models based on Sample B will be run in the next chapter to study the effects of the pandemic and socio-demographics on travel probability for each travel purpose and to verify the mentioned hypotheses.

5. Regression Analysis

This chapter will study the pandemic's impact on the probability of travelling for the given purposes: working, leisure, shopping, and visiting. Socio-economic and demographic attributes of respondents are included in basic models. Specifically, potential disparities in social status and regional development are of interest. Later, interaction terms will be added to basic models to see if the effects of specific socio-demographic variables relied on the effects of the pandemic. We will have discussion and make conclusions in Chapter 6.

5.1. Variables

As section 4.2 reveals, in each year, **only a small fraction** of people carried out a certain type of travel activity on the given day. This partly depends on whether the day surveyed is a weekday or weekend, or whether the respondent is on holiday, but also employment status and other factors.

As Table 4-4 indicates, there was **a decline in diversity of travel activities** – people used to have **1.18** travel purposes per day on average, but the number was down to only **1.01** per day in 2020. Therefore, it would be of interest to investigate…

> **whether a given type of travel activity (work/ leisure/ shopping/ visit) happened or not**.

If not, the value was recorded as **"0"**; otherwise, **"1"**. The outcome binary variable would also reflect the probability of travel, so **"travel probability"** will be used to describe the dependent variable in following interpretation of model results.

There will be one **basic model** for each travel purpose to examine the influencing factors. A **full model** with interaction terms is prepared for each travel purpose and comparison will be made with the basic model. Thus, there will be 8 models in total, with 2 models for each travel purpose.

Independent variables include:

1) Core variables of interest,
    a. to reflect the impact of the pandemic and policies to handle it: **Month groups** (*abbr. MG*) – group A-F in both years, 12 classes in total.
    b. to reflect the effects of social class / social status: **Income group** is chosen here (*abbr. IC*).
    c. to reflect the potential disparity in regional development or spatial settings: **Urbanity level** (*abbr. UC*), recorded as urban-rural continuum.
2) Other controlling variables:

Table 5-1. Controlling variables of regression models.

Other variables *that might also reflect social status*	**Individual socio-demographics**	**Household characteristics**
Education level (*EDU*)	***Age groups*** (reclassified) (abbr. *AG*). **Gender** (*SEX*).	**Number of household members** (*abbr. HM*).

	Ethnicity/Immigration background (*abbr. IB*). **Social participation** (*abbr. SP*). **Whether holding a driving license** (*abbr. DL*).	**Household composition** / structure (*abbr. HS*). **Number of cars in household** (*AUTO*).

These variables offer a complete picture of the respondents, and thus form a good subset of the original data set.

Considering the great number of observations, **the significance level α is set at 0.01**.

Note: all these mentioned variables are categorical variables.

5.2. Basic models

The basic regression model results are shown in Table 5-2.

5.2.1. The probable impacts of the pandemic

Hypotheses in Chapter 4 are partially confirmed by the results, but they are not entirely true. All month groups of 2020 (including the pre-pandemic MA-2020) were significantly correlated with work travel's outcome variable, while only some of them were correlated with other three travel purposes. But these coefficients and significance correspond to the descriptive patterns in section 4.3.

Coefficients for all month groups of 2020 on work travel were **negative**. All but two month-groups (both in 2020) were **positive** for leisure travel. All coefficients of month groups in 2020 for visit travel were **negative**, four of which held significant correlations. **Only one** month group, MC-2020 (i.e., Apr – May) was **negatively** and significantly correlated with shopping travel; other coefficients were close to zero. These results match the finding in the graphs of section 4.3 where work travel witnessed a drastic decline (and a less serious decline for visit travel), leisure travel probability saw a different change, and shopping probability remained rather flat in general.

The severity of the decline of work and visit travel activities can be quantitatively described from the coefficients. For example, in MC-2020, the most serious period of the first wave, odds for people taking at least one work-related trip were 71.1% less than beginning of the year ($e^{-1.377-(-0.137)} - 1 = -0.711$), and odds for visit travel saw a 51.9% decline when compared to MA-2019[6]. Summertime was a typical holiday season, so work travel held a negative significance in MD-2019. By comparison, the odds for work travel in the same period of 2020 were still 56.3% less than last summer ($e^{-1.089-(-0.261)} - 1 = -0.563$), which implies the magnitude of the disruption that the pandemic brought on the economy. The coefficient for visit travel in the same period was only -0.058, suggesting that this activity has almost returned to normal, though the coefficient was not significant.

[6] Since both MA-2020 and MC-2020 were not significantly correlated with the outcome variable of visit travel, the reference level (MA-2019) was used for comparison in the text.

Table 5-2. Basic regression model results for four travel purposes

Coef. (SE)	**Work**			**Leisure**			**Shopping**			**Visit**		
(Intercept)	**0.764**	***	(0.128)	**-1.675**	***	(0.111)	**-1.735**	***	(0.123)	**-2.345**	***	(0.146)
Month group (MG)		*ref. MA-2019*										
MA-2020	**-0.137**	***	(0.040)	0.080	*	(0.033)	0.049		(0.036)	-0.018		(0.045)
MB-2019	0.099		(0.051)	0.022		(0.042)	-0.001		(0.045)	-0.092		(0.057)
MB-2020	**-0.792**	***	(0.050)	**-0.132**	**	(0.041)	-0.092	*	(0.044)	**-0.553**	***	(0.062)
MC-2019	0.061		(0.043)	**0.123**	***	(0.035)	0.010		(0.038)	-0.072		(0.048)
MC-2020	**-1.377**	***	(0.042)	0.035		(0.032)	**-0.162**	***	(0.035)	**-0.732**	***	(0.048)
MD-2019	**-0.261**	***	(0.039)	0.064	*	(0.032)	-0.013		(0.034)	0.009		(0.043)
MD-2020	**-1.089**	***	(0.038)	**0.115**	***	(0.031)	0.058		(0.033)	-0.058		(0.041)
ME-2019	0.009		(0.051)	0.039		(0.042)	-0.108	*	(0.046)	-0.095		(0.058)
ME-2020	**-0.791**	***	(0.050)	**0.147**	***	(0.040)	-0.016		(0.044)	**-0.162**	**	(0.057)
MF-2019	-0.035		(0.037)	0.003		(0.031)	3.61E-03		(0.033)	0.005		(0.041)
MF-2020	**-1.091**	***	(0.038)	-0.065	*	(0.031)	-0.032		(0.033)	**-0.366**	***	(0.043)
Urbanity level (UC)		*ref. least urbanized/ rural (U4)*										
U3 (moderately urbanized)	0.012		(0.027)	0.042	*	(0.022)	**0.114**	***	(0.024)	-0.011		(0.030)
U2 (highly urbanized)	-0.053	*	(0.023)	0.014		(0.018)	**0.170**	***	(0.020)	**-0.102**	***	(0.026)
U1 (most strongly urbanized)	**-0.131**	***	(0.025)	0.042	*	(0.020)	**0.226**	***	(0.022)	**-0.136**	***	(0.028)

Income groups (IC)		*ref. low-income (IC1)*										
IC2 (middle-income)	**0.099**	***	(0.027)	**0.122**	***	(0.020)	0.038		(0.021)	**0.106**	***	(0.029)
IC3 (high-income)	0.026		0.028	**0.223**	***	0.022	0.000		0.023	**0.164**	***	0.031
Gender (SEX)		ref. female										
Male	**0.248**	***	(0.018)	**-0.096**	***	(0.015)	**-0.349**	***	(0.016)	**-0.186**	***	(0.020)
Age group (AG)		*ref. young adults (18-29 yrs., AG2)*										
AG3 (30-64 yrs., middle-aged)	**-0.293**	***	(0.026)	-0.011		(0.023)	**0.262**	***	(0.026)	**-0.508**	***	(0.029)
AG4 (≥65 yrs., old people)	**-0.725**	***	(0.052)	**-0.297**	***	(0.039)	-0.090	*	(0.042)	**-0.790**	***	(0.054)
Ethnicity (IB)		ref. Dutch background (IB1)										
IB2 (western background)	**-0.165**	***	(0.029)	**-0.114**	***	(0.023)	-0.055	*	(0.024)	**-0.205**	***	(0.034)
IB3 (non-western background)	**-0.219**	***	(0.028)	**-0.520**	***	(0.025)	**-0.334**	***	(0.026)	**-0.431**	***	(0.037)
Social participation (SP)		*ref. full-time worker (30 or more hours per week)*										
Part-time worker (work 12-30 hours per week)	**-0.254**	***	(0.025)	**0.145**	***	(0.022)	**0.313**	***	(0.024)	**0.218**	***	(0.030)
Students	**-0.624**	***	(0.038)	**0.272**	***	(0.034)	0.046		(0.039)	**0.209**	***	(0.043)
Retired/VUT	**-2.577**	***	(0.053)	**0.502**	***	(0.035)	**0.657**	***	(0.037)	**0.360**	***	(0.050)

Unemployed and others	**-2.069**	***	(0.033)	**0.228**	***	(0.024)	**0.427**	***	(0.025)	**0.185**	***	(0.034)
Education level (EDU)		*ref. lower level, primary, or no education (EDU1)*										
EDU2 (middle level, e.g., HAVO)	**0.116**	***	(0.027)	**0.300**	***	(0.021)	**0.303**	***	(0.022)	**0.195**	***	(0.029)
EDU3 (higher vocational education or university)	**-0.117**	***	(0.027)	**0.522**	***	(0.020)	**0.343**	***	(0.022)	**0.205**	***	(0.029)
EDU5 (other kinds of training)	**-0.175**	**	(0.060)	-0.027		(0.044)	-0.034		(0.046)	**-0.296**	***	(0.070)
Number of household members (HM)		*ref. 1*										
2	0.104		(0.110)	0.122		(0.097)	-0.058		(0.108)	-0.076		(0.125)
3	0.082		(0.112)	0.100		(0.098)	-0.124		(0.110)	-0.144		(0.127)
4	0.087		(0.114)	0.137		(0.100)	-0.152		(0.112)	-0.232		(0.130)
≥5	0.125		(0.116)	0.147		(0.102)	-0.123		(0.114)	-0.257		(0.133)
Household structure (HS)		*ref. Couple with children*										
Couple without children	0.023		(0.062)	0.048		(0.053)	-2.85E-03		(0.057)	-0.015		(0.074)
Single parent with children	0.075		(0.052)	-0.085		(0.046)	0.067		(0.049)	0.097		(0.063)
Single-person household (and others)	0.213		(0.112)	0.094		(0.098)	-0.020		(0.110)	**0.353**	**	(0.127)

Number of cars in household (AUTO)	*ref. 0*											
1	**0.164**	***	(0.030)	-0.019		(0.024)	-0.042		(0.025)	**0.113**	***	(0.033)
2	**0.235**	***	(0.035)	-0.041		(0.028)	**-0.086**	**	(0.030)	**0.120**	**	(0.039)
≥3	**0.352**	***	(0.043)	-0.063		(0.036)	**-0.103**	**	(0.039)	0.124	*	(0.050)
The respondent holding a driving license (DL)	*ref. No*											
Yes	**0.212**	***	(0.029)	**0.356**	***	(0.023)	**0.280**	***	(0.024)	**0.385**	***	(0.033)
Weekday (WD)	*ref. Monday*											
Sunday	**-2.762**	***	(0.041)	**0.528**	***	(0.025)	**-0.582**	***	(0.030)	**1.064**	***	(0.036)
Tuesday	**0.089**	**	(0.029)	0.051	*	(0.026)	0.014		(0.028)	0.085	*	(0.042)
Wednesday	**-0.124**	***	(0.029)	**0.098**	***	(0.026)	0.058	*	(0.028)	**0.294**	***	(0.041)
Thursday	0.035		(0.029)	**0.075**	**	(0.026)	**0.133**	***	(0.028)	**0.210**	***	(0.041)
Friday	**-0.322**	***	(0.029)	**0.089**	***	(0.026)	**0.441**	***	(0.027)	**0.546**	***	(0.039)
Saturday	**-2.180**	***	(0.036)	**0.393**	***	(0.025)	**0.760**	***	(0.026)	**1.024**	***	(0.037)
Bank holiday status (FD)	*ref. No*											
Yes	**-1.710**	***	(0.080)	-0.077		(0.045)	**-0.766**	***	(0.061)	**0.819**	***	(0.053)

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

5.2.2. Effects of urbanity levels and income groups

We had two interested factors, income and urbanity level, which indicate social class and spatial difference, respectively. From the results, it can be seen that income group was a better predictor for leisure travel, while urbanization class explained shopping travel probability better. Only middle-income group was a significant predictor for work travel but not high-income group, which was out of expectation. While the patterns of work travel of urbanity levels did not differ with each other greatly, the most highly urbanized municipalities still possessed a significance in the model. And it seems that both urbanity level and income were good predictors of visit travel.

Main findings:

(1) The more urbanized the city where people lived, the more likely that they would take a shopping trip. The longer distance and time cost might partly explain the difference in the shopping habit for people from less urbanized spatial settings.
(2) Probability of visit travel increased with levels of income but decreased with the level of urbanization of the city. Maybe rural residents have more and closer social connections.
(3) Higher-income people were more likely to travel for work, but this effect was not significant. Residents from the most strongly urbanized areas had lower probability to have work-related travel than rural residents, which might imply the **difference in occupation** and **the capabilities of remote working** (Brough, et al. 2021).
(4) The higher the level of income, the more likely people would have recreational travel, which is common sense.

It is worth noting that <u>education level</u> (except *EDU5*, i.e., other training) <u>was a **better** predictor for **all travel purposes** than income</u>. The higher education level, the higher odds for people to have recreational, visiting, and shopping travel. The positive coefficients for shopping were beyond expectation. It might contradict our typical perception that better-educated people might shift to online shopping.

The coefficients for work travel were also a bit of strange, where middle-level educated people were more likely to go out for work than lower-educated people but also people with higher education. One possible conjecture is that least-educated people already had bad or no jobs before the pandemic, and their employment status became even worse in the pandemic, as many of them might held jobs in the contact-based service sector that was closed during the outbreak. On the other hand, the best-educated group might enjoy the technological advantages for work-from-home (WFH), or they had flexible schedules of working, so they did not need to travel for work every workday. Or maybe many middle-income occupied frontline medical jobs. All in all, these guesses *lacked enough evidence to support*. Whether the effects of education level and income class have interactions with the pandemic effects is to be tested in Section 5.3.

5.2.3. Effects of other demographic factors

Some socio-demographic attributes appeared to be **perfect** predictors for all kinds of travel activities, including gender, age groups, immigration background, and social participation. Men were more likely to travel out for work than women, but less likely to travel for either recreational purpose or shopping or visiting purposes. The elderly (above 65) were less likely to travel for all purposes than younger people, except the insignificance in shopping, whose coefficient was still negative (-0.09, odds ratio = $e^{-0.09} - 1 = -0.086$) but small in absolute value. This may partly because that the reference level was young adults aged from 18 to 29 years old. The main group of daily groceries purchasing should be the middle-aged workforce, and they ***were*** significantly more likely to do so. The probability of leisure travel did not differ significantly between young adults and middle-aged people, which corresponds to some opinion that 'the Dutch are really outdoor-active people' (CBS News, 2020).

The social participation factor reflected the employment status of people. All other classes, no matter part-time workers, students, retired, or unemployed, were more likely to travel for relaxation and less likely to travel for work than full-time workers. The effects were especially strong for the retired. These groups of people also had higher odds for shopping and visiting travel, though the coefficient of students was not significant in the case of shopping.

We also find that immigration background **did matter**. Even people with western background had less probability to travel than Dutch people for nearly all purposes, not to mention the non-western people. The odds for people with non-western background were 19.7% less than native people in terms of work travel and even 40.5% less for leisure travel. This phenomenon was confirmed by Eftekhar, Creemers, and Cools (2016) in Belgium before the pandemic. Perhaps the ethnicity indicator is more important in predicting travel behaviour and reflecting social disparity.

Household demographics were not good predictors in the models. Only single-person household was positively significantly associated with visit travel probability. Economic factors, however, did matter. Car ownership in the household was a good predictor for work travel. More cars owned in the family, higher probability to commute or have professional trips on the car. The factor was also negatively associated with shopping travel and positively correlated with visiting (though some insignificance did exist). Car ownership did not explain leisure travel well. In contrast, the capability to drive a car of the respondents themselves was a much better predictor that people holding a driving license had higher willingness to travel for all purposes.

5.2.4. Time effects

As what is mentioned in the beginning of section 5.1, since the survey only recorded a one-day diary for every person in the sample, contingency did exist. Whether people travelled for the given purpose on the surveyed day did depend on temporal factors like weather, illness, weekdays, and so on. Therefore, the variables ‘weekday’ and ‘bank holiday’ should be included in models.

Results show that weekend days (Sat. & Sun.) and Fridays were perfect predictors for all travel activities. Tuesdays only explained work travel probability well. Thursday possessed significance for all purposes but work, which is reasonable as Thursdays are typical shopping nights when stores delay closing in the Netherlands. Wednesdays fit in all purposes well except shopping travel. Its positive coefficient for work and negative for leisure travel might be linked with the early class-off time of children. Overall, weekdays were good predictors for all travel purposes.

Only 10 days serve as bank holidays in the Netherlands, so it does affect people’s travel behaviour. Results indicate that this factor was significantly associated with all types of travel activities except leisure travel, which is unexpected as we all believe people have more entertainment trips on bank holidays (e.g., Koningsdag) in general.

5.2.5. Power of the models

It is of importance to examine how much ‘variation’ the logistic regression model can explain and how much it has improved from the null model. There are some most-used parameters for exploration, such as AIC, log-likelihood, and pseudo-R^2, as shown in Table 5-3. With an identical sample and same selection of independent variables, values of these indicators can be compared directly across models.

McFadden pseudo-R-squared is one of the most-used indicators. When it is between 0.2 to 0.4, we can conclude that the model is a good fit. Thus, the model explains the work travel well in general.

Smaller Akaike Information Criterion (AIC) value or a larger log-likelihood usually implies a better model fitness. In this sense, visit travel model has the best goodness of fit, even a little better than work-travel model. The model for shopping shows better fitness than model for leisure travel, but both are a lot weaker than models for work or visit travel.

Table 5-3. Goodness-of-fit indicators of all basic models.

Indicators	Work	Leisure	Shopping	Visit/Stay
Observations		98459		
AIC	85583	125289	111730	***74258***
Log Likelihood (df=47)	-42744.3	-62597.7	-55818.0	***-37081.8***
McFadden R^2	***0.2985***	0.0278	0.0462	0.0554

Overall, in terms of basic models (without interaction effects), the models for work and visit travel probability showed better goodness of fit than other travel purposes.

5.3. Full models with interaction terms

Significant predictors could be drawn from Table 5-2 for each travel purpose. Income group, education level, and urbanization class are the key variables to test the hypotheses. Thus, only interaction terms between these three variables and month-groups that showed significance will be added to the basic models to investigate the possible interaction effects between the pandemic (month-groups) and factors that may reflect social and spatial disparity. The following section is to discuss the main results of the interaction terms.

5.3.1. Work travel

Five month-groups post-pandemic and five significant socio-demographic factors of interest together formed 25 interaction terms. Income group became almost insignificant after interaction (Table 5-4). Only one significance factor remained in interaction between MF-2020 (Oct-Dec) and middle-income group. Other interactions with income showed no significance. In contrast, the most strongly urbanized areas (**U1**), plus higher-education level (**EDU3**), were two most important factors that all month-groups they interacted with possessed significance. The most urbanized residents had significantly lower odds for work travel under the impacts of **pandemic** (all month-groups post-COVID). People of all education levels were less likely to travel for work than least-educated group under the impacts of **both waves of the pandemic**. The negative effects for work-related trips were even stronger and more significant for people with high-level education (esp. MC- & MF-2020).

Table 5-4. Interaction terms of work travel probability model

Month group (*ref.= MA_2019*)	Urbanization Class, *ref=U4 (rural)*	Income group, *ref=IC1 (low-income)*	Education level, *ref=Edu1 (low-level)*		
	Most strongly urbanized (U1) 0.012	Middle-income (IC2) 0.045	Middle-level (EDU2) 0.212 ***	High-level (EDU3) 0.188 ***	Other trainings, (EDU5) -0.083
MB-2020 -0.276 *	MB_20×U1: -0.301 **	MB_20×IC2: -0.022	MB_20×Edu2: -0.26 *	MB_20×Edu3: -0.713 ***	MB_20×Edu5: -0.416
MC-2020 -0.862 ***	MC_20×U1: -0.352 ***	MC_20×IC2: +0.134 *	MC_20×Edu2: -0.224 *	MC_20×Edu3: -0.85 ***	MC_20×Edu5: -0.235
MD-2020 -0.639 ***	MD_20×U1: -0.351 ***	MD_20×IC2: +0.089	MD_20×Edu2: -0.266 **	MD_20×Edu3: -0.626 ***	MD_20×Edu5: -0.093
ME-2020 -0.518 ***	ME_20×U1: -0.443 ***	ME_20×IC2: +0.117	ME_20×Edu2: -0.113	ME_20×Edu3: -0.335 **	ME_20×Edu5: -0.314
MF-2020 -0.481 ***	MF_20×U1: -0.297 ***	MF_20×IC2: +0.235 ***	MF_20×Edu2: -0.389 ***	MF_20×Edu3: -1.024 ***	MF_20×Edu5: -0.358

As for pandemic effects, four of five interaction terms between MF-2020 (Oct – Dec) and socio-demographic factors held significance. Interaction between MD-2020 (Jun – Aug) of summertime and middle-level education also showed negatively significant effects, indicating that even when measures were partially relaxed, people did not go back to offices (Note: this may require further confirmation by adding an interaction term with MD-2019).

The result of the likelihood ratio test (LRT) showed that the Chi-square value was 526.78 at the degree of freedom of 25 ($\chi 2$ = 526.78***, df = 25, Pr(X> $\chi 2$) < 0.001), which meant there was a significant improvement from the basic model after adding the interaction terms. This result supported the existence of social and spatial disparity, and this disparity was even exacerbated under the pandemic conditions.

5.3.2. Leisure travel

Almost all coefficients for the 12 interaction terms (between income or education and three month-groups) were positive (with the exception of "EDU3 × MB-2020" & "EDU3 × MD-2020") but only one interaction term possessed significance (Table 5-5): the interaction between MD-2020 and high-income group. The same summertime period in 2019 was not significant in the original basic model so was not added to this model. Therefore, it is not sure if this positively significant effect was due to the relaxation of the pandemic controlling measures or merely the holiday effect. There were still border controls to some extent in summer 2020 to contain the spread of virus, and this might increase the odds of people having their vacations within the Netherlands instead of abroad, thus leeading to a positive coefficient for leisure travel probability.

As the new model appeared not to be a better fit than the basic model ($\chi 2$ = 18.334, df = 12, Pr(X> $\chi 2$) = 0.106), the interaction effects we just discussed can be neglected.

Table 5-5. Interaction terms of leisure travel probability model

Month group (*ref.= MA_2019*)	Income group, *ref=IC1 (low-income)* Middle-income (IC2) 0.045	High-income (IC3) 0.026	Education level, *ref=Edu1 (low-level)* Middle-level (EDU2) 0.212 **	High-level (EDU3) 0.188 **
MB-2020 -0.158	MB_20×IC2: +0.043	MB_20×IC3: +0.078	MB_20×Edu2: +0.029	MB_20×Edu3: -0.071
MD-2020 -0.003	MD_20×IC2: +0.072	MD_20×IC3: +0.181 **	MD_20×Edu2: +0.052	MD_20×Edu3: -0.003
ME-2020 -0.016	ME_20×IC2: +0.116	ME_20×IC3: +0.135	ME_20×Edu2: +0.056	ME_20×Edu3: +0.093

5.3.3. Shopping travel

Only one month-group (MC-2020) had a significant correlation with shopping travel probability. The table of interaction (Table 5-6) showed that education was the *exact* variable whose effects depend on the impacts of the pandemic (first wave). These interaction terms showed positive association with shopping travel probability. Higher level of education increased the odds for people to make shopping travel in the most serious stage of the epidemic, which was not the case in some existing research (Chang, et al., 2020). Perhaps worse-educated people also suffered from shortage of medical resources and were more frightened to get infected than better-educated citizens, and thus reduce their frequency of groceries purchases in supermarkets to avoid the crowds.

Table 5-6. Interaction terms of shopping travel probability model

Month group (*ref.= MA_2019*)	Urbanization Class, ref=U4 (rural)			Education level, ref=EDU1 (low-level)	
	Moderately urbanized (U3) 0.114 ***	Highly urbanized (U2) 0.174 ***	Most strongly urbanized (U1) 0.226 ***	Middle-level (EDU2) 0.279 ***	High-level (EDU3) 0.315 ***
MC_2020 -0.351 ***	MC_20 × U3: -0.009	MC_20 × U2: -0.049	MC_20 × U1: -0.008	MC_20 × Edu2: +0.247 ***	MC_20 × Edu3: +0.291 ***

The likelihood ratio test confirmed that there was a significant improvement after these five interaction terms were added to the model ($\chi2$ = 23.17***, *df* = 5, Pr(X> $\chi2$) = 0.0003). Therefore, adding interaction between education level and MC-2020 would better explain the shopping travel probability in the Netherlands, especially in the pandemic situation.

Table 5-7. Interaction terms of visiting travel probability model

Month group (*ref.= MA-2019*)	Urbanization Class, ref=U4 (rural)		Income group, ref=IC1 (low-income)	
	Highly urbanized (U2) -0.085 **	**Highest urbanized (U1)** -0.131 ***	**Middle-income (IC2)** +0.094 **	**High-income (IC3)** +0.145 ***
MB-2020 -0.561 **	MB_20×U2: -0.038	MB_20×U1: -0.083	MB_20×IC2: 0.101	MB_20×IC3: 0.103
MC-2020 -0.962 ***	MC_20×U2: -0.092	MC_20×U1: -0.066	MC_20×IC2: 0.152	MC_20×IC3: 0.072
ME-2020 -0.21	ME_20×U2: -0.122	ME_20×U1: +0.016	ME_20×IC2: 0.139	ME_20×IC3: 0.177
MF-2020 -0.422 ***	MF_20×U2: -0.032	MF_20×U1: +0.022	MF_20×IC2: -0.075	MF_20×IC3: 0.025

Month group (*ref.= MA-2019*)	Education level, ref=Edu1 (low-level)		
	Middle-level (Edu2) 0.173 ***	**High-level (Edu3)** 0.181 ***	**Other trainings (Edu5)** -0.267 ***
MB-2020 -0.561 **	MB_20×Edu2: -0.01	MB_20×Edu3: -0.096	MB_20×Edu5: 0.215
MC-2020 -0.962 ***	MC_20×Edu2: 0.206	MC_20×Edu3: 0.264 *	MC_20×Edu5: -0.3
ME-2020 -0.21	ME_20×Edu2: -0.037	ME_20×Edu3: -0.077	ME_20×Edu5: -0.135
MF-2020 -0.422 ***	MF_20×Edu2: 0.087	MF_20×Edu3: 0.11	MF_20×Edu5: -0.136

5.3.4. Visit travel

28 interaction terms were constructed by multiplying four month-groups under two waves of outbreak and seven sociodemographic factors of interest (Table 5-7). However, likelihood ratio test proved that the new model was not a good fit ($\chi2$ = 24.597, *df* = 28, Pr(X> $\chi2$) = 0.650), and ***NO*** interaction terms held significance. This finding accorded with the general impression from the graphs that visit travel was seriously disrupted but effects on income or urbanity levels did not differ

significantly, and thus confirmed the hypothesis. The basic model, therefore, is a better fit for explanation of daily visiting travel.

5.4. Summary of regression analysis

The regression model results conveyed much useful information. From the analysis, some key conclusions can be made:

1) Full models with interaction terms were better fit for the explanation of work and shopping travel probability, while the model without interaction effects worked better for leisure and visit travel patterns.
2) Horizontal comparison between basic models of four travel purposes suggest that work and visit travel models had a better goodness of fit, while the leisure model was the worst in explaining the patterns.
3) Most income groups and urbanity levels were significant factors on travel probability for all purposes. Education level may be a better predictor than income with stronger significance and it also indicates potential social disparity.
4) Results show that the controlling variables (which were not our primary research interest) like gender, immigration background, social participation, household car ownership, and possession of driving license, were more powerful predictors in explaining the travel probability of all purposes.
5) Regression models in this chapter verify most of the assumptions made in Section 4.3.4, which is to be discussed in detail in next chapter.

6. Concluding remarks

6.1. Conclusions

This study uses the results of Dutch National Travel Survey (ODiN) to investigate mobility changes in the first and second wave of COVID-19 pandemic in the Netherlands and propose potential factors that led to differentiated effects on travel for different purposes. Conclusions are drawn as follows.

(1) General changes

The work-related travel was the most extremely disrupted, seeing a dramatic decrease in both distance/time travelled and frequency of work trips. In contrast, leisure travel offered a different picture. Leisure travel distance fell considerably, while travel time saw an opposite trend. Probability of leisure travel in 2020 stayed largely the same with that in 2019.

The changes in shopping travel were the smallest among all travel purposes, and its travel probability[7] remained around 27% during the pandemic, similar to that of last year.

Visit/Stay was the activity that was the least probable to take place, with an average probability below 15% in both years. Generally, the patterns of visit/stay travel distance/time share commonality with that of work travel, with the lowest points observed amid the initial outbreak of pandemic and highest points in summer when measures were eased.

(2) Variation in income (education) and urbanity levels

From descriptive statistics, the differentiated effects of income classes on travel for work-related purposes during the pandemic were the most distinct (Fig. 4-2). As for other travel purposes, the variation across income groups was much smaller. The variations across urbanization levels were even smaller for all purposes (Fig. 4-3), and the curves were too fluctuating to interpret. Thus, assumptions were made in the end of Chapter 4 that urbanity level might not be a significant factor in predicting the travel probability of the investigated purposes.

The binary logistic regression results partially confirm the assumptions. Not all month groups post-outbreak held significance in models for purposes except working. Urbanity levels were all significant in predicting shopping travel probability, and partly significant in interpreting work and visit travel, which was not within prediction. Income levels could significantly impact leisure and visit travel probability, and middle-income people are significantly more likely to travel for work than the low-income.

By comparison, socio-demographic factors such as gender, immigration background, social participation, and, specifically, **level of education**, showed *greater* significance in predicting the probability for *all* travel purposes. Thus, **education level might be a better predictor to reflect disparity in social status**.

[7] The concept of travel probability was defined in section 4.3

Interestingly, low-income people travelled substantially less than middle- and high-income people regardless the existence of the pandemic. Though the extent of decrease in work travel among low-income people was stronger, the recovering speed of low-income people was also lower. One possible explanation is that low-income people do not own a car in household and have limited travel budget, which supressed their travel demand and capability. Pandemic might worsen their economic status and so their mobility remained at low level after the outbreak, even when the measures relaxed. Fear of contagion and low ability to cover medical fares might also supress their intention for non-essential trips.

(3) Interaction between social status/spatial setting variables and time periods

Months were divided into six groups each year according to the situation of COVID-19 in the Netherlands, thus representing the pandemic effects in the models. In basic models, many month-groups in 2020 (esp. after the outbreak in spring) possessed significance in predicting the outcomes. Therefore, we run models with interaction terms to examine the dependency of the independent variables of our research interest (income/education/urbanity) on the pandemic.

Regarding work travel probability, the results show that high-education (EDU3) and most-strongly-urbanized (U1) possessed significance in interaction with all month groups (MB ~ MF). This means that the variation effects of both attributes partly relied on the pandemic effects, i.e., the difference was significant during the pandemic (March to December) between the highest urbanized residents and respondents living in the least urbanized areas, and between people with high level of education and those with low level of education.

Significance was also found in interaction between MC-2020 (first-wave) and education levels in the model of shopping.

However, models for other purposes did not show similar significance, and their goodness of fit is worse than their basic models. In contrast, significant improvements were found in work and shopping models.

By descriptive analysis and regression modelling, this thesis found the mobility decline caused by COVID-19 pandemic was considerable, and disparity between income/education and urbanity levels were partly confirmed (though it was not expected that education was a better predictor than income). The thesis contributes to the understanding of the impact of a sudden life event on mobility and out-of-home activity patterns, and provide empirical implication for policy making.

6.2. Limitation of the research

The limitations of the thesis include:

(1) Weighting of the sample.

The share of income deciles in the sample is not representative enough and should be adjusted before analysis.

Furthermore, the survey is in fact divided into basic and additional surveys, but their results were merged into one CSV file. The additional surveys were carried out in several given regions. In 2019, it was Metropolitan Areas of Amsterdam and Rotterdam-The Hague, while in 2020, Utrecht Province and ParkStad of Limburg were added. Therefore, the weightings of regions in 2019 and 2020 were far from the same. To ensure enough cases in the analysis, I did not distinguish additional survey results from the basic ones, which led to biases in the sample. Further analysis is required to examine if the findings in this survey were twisted.

(2) Survey design.

The large-sample survey carried out every year by the Dutch government had its limitation. For example, the questionnaires did not include COVID-specific questions in 2020. Specifically, the sector occupation of the respondent was not investigated. The groceries shopping purpose was not distinguished from general shopping (Beck & Hensher, 2020a). Including these indices would bring more interesting findings since they could be compared with existing research results, as essential workers and essential travel would be detected (Fatmi, et al., 2021; Chen, et al., 2021).

The survey is a cross-sectional one rather than longitudinal, making it difficult to compare the real intra-personal changes. Moreover, this survey only requires reporting of one-day travel diary, the duration of which is so short that will increase contingency and instability of results. By comparison, there were studies requiring three-day (De Haas, et al., 2020) or even one-week (Shaer & Haghshenas, 2021) travel diaries. This design of survey (in ODiN) will contribute to systematic errors.

(3) Choice of models and goodness of fit

Binary logistic regression was chosen to analyse travel probability for given travel purposes (work, leisure, shopping, and visit/stay). However, goodness of fit of all models were generally low (except that for working travel). This probably implies that the socio-demographic predictors were not chosen properly. Tobit or zero-inflated models could be applied to investigate the relationship between travel distance or time and predictors used in this thesis.

6.3. Recommendations

Empirically, this thesis presents the patterns for different travel purposes and reveals the disparity in social status (education level) and spatial settings under the disruption of COVID-19 pandemic. The findings have following implications for policy making:

a) The neighbourhood played an important role in the emergency under intelligent lockdown, which is confirmed by the noticeable increase in leisure travel around the neighbourhood in MC-2020 (April to May), providing necessary relaxing experience to help people get past those dark periods. In this sense, greening the built environments can be beneficial to residents' mental health and boost interactions between neighbours, and such positive effects can last after COVID-19 crisis.

b) The low travel level of low-income people suggests their limited capability of mobility and potential unemployment due to closure of contact-based services and shrinkage of transportation service industry (e.g., aviation). On the one hand, governments should pay attention to the living conditions and distribute unemployment benefits or special public transportation bundles to targeted vulnerable groups. On the other hand, governments should provide safe transport options with regular disinfection in response to their concern of the pandemic.

c) Shopping travel showed resilience in the pandemic time and should be attached with more importance in the future. Reduce crowding in the supermarkets and shopping malls and regularly do the hygiene job could help release fear of contagion. Make the shopping sites more accessible to all social classes to cut down the shopping travel cost for low-income people. These are jobs we can do to improve shopping experience, promote social justice, and make it more resilient to face with future challenges.

Academically, this thesis is the first to examine the correlation between pandemic and different travel purposes in the Dutch (European) context. Existing studies tend to focus on modal shifts and travel frequency. Thus, this research fills the research gap of understanding the effects of pandemic on different travel activities. In future, people can investigate the modal choice change within specific travel activities, such as work-related and recreational travel. Frequency of trips and distance and time travelled are also worth studying.

The impact of COVID-19 on mobility patterns was full-scale, sometimes not differing between different social-demographic group. It will be interesting if additional variables are added to study the effects of the restrictive measures and fear of pandemic separately, as some have done previously (Engle, et al., 2020).

Additionally, a theoretical review of travel behaviour in section 2.1 discussed in detail whether the impact of pandemic on mobility is structural long-term or temporary. As the pandemic finally almost comes to an end, it is of importance to fully gather the mobility data over the last three years to verify the hypothesis whether the influence is temporary or not.

Bibliography

Abdullah, M., Ali, N., Hussain, S. A., Aslam, A. B., Javid, M. A. (2021) Measuring changes in travel behavior pattern due to COVID-19 in a developing country: A case study of Pakistan. *Transport Policy, 108, 21–33.* https://doi.org/10.1016/j.tranpol.2021.04.023.

Aronna Cruz, V. (2021). An activity-based modeling approach to assess the effects of activity-travel behavior changes and in-home activities on mobility: Estimations based on different stages of the COVID-19 pandemic in the Rotterdam-The Hague Metropolitan Area. *Delft University of Technology, Delft, the Netherlands.*

Backer, J. A., Mollema, L., Vos, E. R., Klinkenberg, D., van der Klis, F. R., de Melker, H. E., van den Hof, S., & Wallinga, J. (2021). Impact of physical distancing measures against covid-19 on contacts and mixing patterns: repeated cross-sectional surveys, the Netherlands, 2016-17, April 2020 and June 2020. *Euro Surveillance: 26(8).* https://doi.org/10.2807/1560-7917.ES.2021.26.8.2000994.

Baig, F., Kirytopoulos, K., Lee, J., Tsamilis, E., Mao, R., & Ntzeremes, P. (2022). Changes in People's Mobility Behavior in Greece after the COVID-19 Outbreak. *Sustainability, 14(6), 3567*, https://doi.org/10.3390/su14063567.

Barbieri, D.M., Lou, B., Passavanti, M., Hui, C., Hoff, I., Lessa D.A., et al. (2021) Impact of COVID-19 pandemic on mobility in ten countries and associated perceived risk for all transport modes. *PLOS ONE, 16(2): e0245886*. https://doi.org/10.1371/journal.pone.0245886.

Beck, M. J. & Hensher, D. A. (2020a) Insights into the impact of COVID-19 on household travel and activities in Australia – The early days under restrictions. *Transport Policy, 96, 76–93.* https://doi.org/10.1016/j.tranpol.2020.07.001.

Beck, M. J. & Hensher, D. A. (2020b) Insights into the impact of COVID-19 on household travel and activities in Australia – The early days of easing restrictions. *Transport Policy, 99, 95–119.* https://doi.org/10.1016/j.tranpol.2020.08.004.

Beck, M. J., Hensher, D. A. (2022). Australia 6 months after COVID-19 restrictions- part 1: Changes to travel activity and attitude to measures. *Transport Policy, 128, 286–298.* https://doi.org/10.1016/j.tranpol.2021.06.006.

Ben-Elia, E. & Ettema, D. (2012). Rewarding rush-hour avoidance: A study of commuters' travel behavior. *Transportation Research Part A, 45 (2011), 567–582.* DOI:10.1016/j.tra.2011.03.003.

Bhat, C. (2020). Why COVID-19 Won't Change Long-Term Travel Behavior. Published on online platform of *Texas Engineering* on *Medium.com* on 22 May 2020. Retrieved on 5 December 2022. https://medium.com/@cockrellschool/why-covid-19-wont-change-long-term-travel-behavior-f39be3db7e3a.

Böcker, L., Dijst, M., & Prillwitz, J. (2013) Impact of Everyday Weather on Individual Daily Travel Behaviours in Perspective: A Literature Review. *Transport Reviews, 33:1, 71-91.* https://doi.org/10.1080/01441647.2012.747114.

Borkowski, P., Jażdżewska-Gutta, M., & Szmelter-Jarosz, A. (2021). Lockdowned: Everyday mobility changes in response to COVID-19. *Journal of Transport Geography, 90, 102906.* https://doi.org/10.1016/j.jtrangeo.2020.102906.

Brough, R., Freedman, M. & Phillips, D. C. (2021). Understanding socioeconomic disparities in travel behavior during the COVID-19 pandemic. *Journal of Regional Science. 61:753–774.* https://doi.org/10.1111/jors.12527.

Carrese, S., Cipriani, E., Colombaroni, C., Crisalli, U., Fusco, G., Gemma, A., Isaenko, N., Mannini, L., Petrelli, M., Busillo, V., Saracchi, S. (2021) Analysis and monitoring of post-COVID mobility demand in Rome resulting from the adoption of sustainable mobility measures. *Transport Policy, 111, 197–215.* https://doi.org/10.1016/j.tranpol.2021.07.017.

CBS (Statistics Netherlands). (2020). Onderweg in Nederland (2019) – Onderzoeksbeschrijving (*in Dutch*, meaning: *research description*).

CBS (Statistics Netherlands). (2021a). Bijna een derde minder kilometers afgelegd in 2020 (*in Dutch*). Published online on 30 June 2021. Retrieved on 5 December 2022. https://www.cbs.nl/nl-nl/nieuws/2021/26/bijna-een-derde-minder-kilometers-afgelegd-in-2020.

CBS (Statistics Netherlands). (2021b). Onderweg in Nederland (2019) – Onderzoeksbeschrijving (*in Dutch*). https://www.cbs.nl/nl-nl/longread/rapportages/2021/onderweg-in-nederland--odin---2020-onderzoeksbeschrijving.

CBS (Statistics Netherlands). (2022). Documentatie onderzoek Onderweg in Nederland 2020 (ODiN2020) (*in Dutch*, meaning: *Research documentation of ODiN*). Published/Renewed on 16 March 2022.

CBS News. Dutch gamble on limited "intelligent lockdown" to control coronavirus. Published on 30 April 2020. Retrieved on 6 December 2022. https://www.cbsnews.com/news/coronavirus-netherlands-gamble-on-limited-intelligent-lockdown-to-control-covid-19/.

Chang, S., Pierson, E., Koh, P.W., Gerardin, J., Redbird, B., Grusky, D., & Leskovec, J. (2020). Mobility network models of COVID-19 explain inequities and inform reopening. *Nature, 589(7840), 82–87.* https://doi.org/10.1038/s41586-020-2923-3.

Chatterjee, K. and Scheiner, J. (2015) Understanding changing travel behaviour over the life course: Contributions from biographical research. Resource paper presented at *the 14th International Conference on Travel Behaviour Research, Windsor, UK*, July 19-23.

Chen, X., Guo, Y., Yang, C., Ding, F., Yuan, Q. (2021) Exploring essential travel during COVID-19 quarantine: Evidence from China. *Transport Policy, 111, 90-97*. https://doi.org/10.1016/j.tranpol.2021.07.016.

Chorus, C., Sandorf, E. D., & Mouter, N. (2020). Diabolical dilemmas of COVID-19: An empirical study into Dutch society's trade-offs between health impacts and other effects of the lockdown. *PLoS ONE 15(9): e0238683*. https://doi.org/10.1371/journal.pone.0238683.

Clark, B., Chatterjee, K., Melia, S., Knies, G., & Laurie, H. (2014). Life events and travel behavior: Exploring the interrelationship using UK household longitudinal study data. *Transportation Research Record, 2413(1), 54–64*. https://doi.org/10.3141/2413-06.

Costa, C.S.; Pitombo, C.S.; de Souza, F.L.U. (2022) Travel Behavior before and during the COVID-19 Pandemic in Brazil: Mobility Changes and Transport Policies for a Sustainable Transportation System in the Post-Pandemic Period. *Sustainability, 14, 4573*. https://doi.org/10.3390/su14084573.

Coven, J. and Gupta, A. (2020). Disparities in mobility responses to COVID-19. (NYU Stern School of Business; *Online, 15/5/2020*). https://static1.squarespace.com/static/56086d00e4b0fb7874bc2d42/t/5ebf201183c6f016ca3abd91/1589583893816/DemographicCovid.pdf.

Das, S., Boruah, A., Banerjee, A., Raoniar, R., et al. Impact of COVID-19: A radical modal shift from public to private transport mode. *Transport Policy, 109, 1–11.* https://doi.org/10.1016/j.tranpol.2021.05.005.

De Haas, M., Faber, R., Hamersma, M. (2020) How COVID-19 and the Dutch 'intelligent lockdown' change activities, work and travel behaviour: Evidence from longitudinal data in the Netherlands. *Transportation Research Interdisciplinary Perspectives 6, 100150.* http://dx.doi.org/10.1016/j.trip.2020.100150.

De Paepe, L.; De Vos, J.; van Acker, V. & Witlox, F. (2018) Changes in travel behavior during the transition from secondary to higher education: A case study from Ghent, Belgium. *The Journal of Transport and Land Use, 11 (1)*: pp. 477-498.

Dutch Government. *Coronavirus Dashboard*: Number of confirmed cases. Online platform, retrieved on 6 December 2022. https://coronadashboard.government.nl/landelijk/positief-geteste-mensen.

Eftekhar, H. Creemers, L., Cools, M., (2016). Effect of Traveller's Nationality on Daily Travel Time Expenditure Using Zero-Inflated Negative Binomial Regression Models: Results from Belgian National Household Travel Survey. *Transportation Research Record: Journal of the Transportation Research Board, 2565: pp. 65-77*. DOI:10.3141/2565-08.

Engle, S., Stromme, J., Zhou, A. (2020) Staying at Home: Mobility Effects of COVID-19. Working paper. https://ssrn.com/abstract=3565703.

Fujii, S., & Kitamura, R. (2003). What does a one-month free bus ticket do to habitual drivers? An experimental analysis of habit and attitude change. *Transportation, 30(1), 81-95.* https://doi.org/10.1023/A:1021234607980.

Gao, J., Ettema, D., Helbich, M., & Kamphuis, C. B. M. (2019). Travel mode attitudes, urban context, and demographics: do they interact differently for bicycle commuting and cycling for other purposes? *Transportation, 46(6), 2441–2463*. https://doi.org/10.1007/s11116-019-10005-x.

Gao, J., Kamphuis, C. B. M., Helbich, M., & Ettema, D. (2020). What is 'neighborhood walkability'? How the built environment differently correlates with walking for different purposes and with walking on weekdays and weekends. *Journal of Transport Geography, 88.* https://doi.org/10.1016/j.jtrangeo.2020.102860.

Gärling, T., & Fujii, S. (2009). Travel behavior modification: Theories, methods, and programs. *The expanding sphere of travel behaviour research, 97-128*.

Iyanda, A., Boakye, K., Lu, Y., & Oppong, J. (2022). Racial/Ethnic Heterogeneity and Rural-Urban Disparity of COVID-19 Case Fatality Ratio in the USA: a Negative Binomial and GIS-Based Analysis. *Journal of Racial and Ethnic Health Disparities, 9, 708–721*. https://doi.org/10.1007/s40615-021-01006-7.

Jenelius, E. & Cebecauer, M. (2020). Impacts of COVID-19 on public transport ridership in Sweden: Analysis of ticket validations, sales and passenger counts. *Transportation Research Interdisciplinary Perspectives 8, 100242.*

Kolarova, V., Eisenmann, C., Nobis, C., Winkler, C. & Lenz, B. (2021) Analysing the impact of the COVID-19 outbreak on everyday travel behaviour in Germany and potential implications for future travel patterns. *European Transport Research Review, 13:27*. https://doi.org/10.1186/s12544-021-00486-2.

König, A., & Dreßler, A. (2021). A mixed-methods analysis of mobility behavior changes in the COVID-19 era in a rural case study. *European Transport Research Review,13:15*. https://doi.org/10.1186/s12544-021-00472-8.

Lu, X., Yang, X., Zhang, J., Han, J. & Li, L. (2022). The travel behavior changes study based on repeatedly fluctuations of COVID-19 – Using residents in Xi'an city as an example. *SSRN Pre-print paper (Not peer-reviewed)*. https://ssrn.com/abstract=4262025.

Meier K, Glatz T, Guijt MC, Piccininni M, van der Meulen M, Atmar K, et al. (2020) Public perspectives on protective measures during the COVID-19 pandemic in the Netherlands, Germany and Italy: A survey study. *PLoS ONE 15(8): e0236917*. https://doi.org/10.1371/journal.pone.0236917.

Mulder C.H. & Hooimeijer P. (1999) Residential relocations in the life course (Chapter 6). In: Wissen van L.J.G. and Dykstra P.A. (eds.), Population Issues. An Interdisciplinary Focus. *The Plenum Series on Demographic Methods and Population Analysis* (pp. 159-186). *New York: Kluwer Academic/Plenum Publishers.*

Nielsen, T. A., Haustein, S., (2019). Behavioural effects of a health-related cycling campaign in Denmark: Evidence from the national travel survey and an online survey accompanying the campaign. *Journal of Transport & Health, 12, 152-163*.

Nouvellet, P., Bhatia, S., Cori, A., Ainslie, K. E. C., Baguelin, M., Bhatt, S., Boonyasiri, A., Brazeau, N. F., Cattarino, L., … Donnelly, C. A. (2021). Reduction in mobility and covid-19 transmission. *Nature Communications, 12(1)*. https://doi.org/10.1038/s41467-021-21358-2.

Pawar, D. S., Yadav, A. K., Choudhary, P., & Velaga, N. R. (2021). Modelling work-and non-work-based trip patterns during transition to lockdown period of COVID-19 pandemic in India. *Travel Behaviour and Society, 24, 46-56*. https://doi.org/10.1016/j.tbs.2021.02.002.

Politis, I., Georgiadis, G., Nikolaidou, A., Kopsacheilis, A., Fyrogenis, I., Sdoukopoulos, A., Verani, E., & Papadopoulos, E. (2021). Mapping travel behaviour changes during the COVID-19 lock-down: a socioeconomic analysis in Greece. *European Transport Research Review, 13:21*. https://doi.org/10.1186/s12544-021-00481-7.

Probst, J. C., Laditka, S. B., Wang, J.-Y., & Johnson, A. O. (2007). Effects of residence and race on burden of travel for care: cross sectional analysis of the 2001 us national household travel survey. *BMC Health Services Research*, *7*(1). https://doi.org/10.1186/1472-6963-7-40.

Schwanen, T., Dieleman, F. M., & Dijst, M. (2001). Travel behaviour in Dutch monocentric and policentric urban systems. *Journal of transport geography, 9(3), 173-186*. https://doi.org/10.1016/S0966-6923(01)00009-6.

Scorrano, M., & Danielis, R. (2021). Active mobility in an Italian city: Mode choice determinants and attitudes before and during the Covid-19 emergency. *Research in Transportation Economics 86, 101031.* https://doi.org/10.1016/j.retrec.2021.101031.

Shaer, A., & Haghshenas, H. (2021) Evaluating the effects of the COVID-19 outbreak on the older adults' travel mode choices. *Transport Policy 112, 162–172*. https://doi.org/10.1016/j.tranpol.2021.08.016.

Song, J., Zhang, L., Qin, Z. & Ramli, M. A. (2022) Spatiotemporal evolving patterns of bike-share mobility networks and their associations with land-use conditions before and after the COVID-19 outbreak. *Physica A, 592: 126819*. https://doi.org/10.1016/j.physa.2021.126819.

Taale, H., Kalter, M. J. O., Haaijer, R., & Damen, C. (2022). The impact of COVID-19 and policy measures on commuting in the Netherlands. *Case Studies on Transport Policy, 10, 2369-2376.* https://doi.org/10.1016/j.cstp.2022.10.018.

Teixeira, J.F. & Lopes, M. (2020) The link between bike sharing and subway use during the COVID-19 pandemic: The case-study of New York's Citi Bike. *Transportation research interdisciplinary perspectives, 6, 100166.*

Ton, D., Arendsen, K., de Bruyn, M., Severens, V., van Hagen, M., van Oort, N., Duives, D. (2022). Teleworking during COVID-19 in the Netherlands: Understanding behaviour, attitudes, and future intentions of train travellers. *Transportation Research Part A, 159, 55–73.* https://doi.org/10.1016/j.tra.2022.03.019.

Von Behren, S., Puhe, M., & Chlond, B. (2018). Office relocation and changes in travel behavior: Capturing the effects including the adaptation phase. *Transportation Research Procedia, 32, 573–584*. https://doi.org/10.1016/j.trpro.2018.10.021.

Van der Drift, S., Wismans, L., & Olde Kalter, M-J. (2022). Changing mobility patterns in the Netherlands during COVID-19 outbreak. *Journal of Location Based Services, 16(1), 1-24.* DOI: 10.1080/17489725.2021.1876259.

Wang, X., Shao, C., Yin, C., & Guan, L. (2020). Built environment, life events and commuting mode shift: Focus on gender differences. *Transportation Research Part D, 88*. https://doi.org/10.1016/j.trd.2020.102598.

Xie, Y. (2010). Regression Analysis (<回归分析>, *in Chinese*). *Social Sciences Academic Press. Beijing, China (社会科学文献出版社)* .

Yamada, E. & Shimizutani, S. (2022) The COVID 19 pandemic, daily mobility, and household welfare: Evidence from Tajikistan. *Transportation Research Interdisciplinary Perspectives, 15, 100641*. https://doi.org/10.1016/j.trip.2022.100641.

Zhang, N., Jia, W., Wang, P., Dung, C.-H., Zhao, P., Leung, K., Su, B., Cheng, R., & Li, Y. (2021). Changes in local travel behaviour before and during the covid-19 pandemic in Hong Kong. *Cities, 112*. https://doi.org/10.1016/j.cities.2021.103139.

Zhang, S., Yang, Y., Zhen, F., Lobsang, T., & Li, Z. (2021). Understanding the travel behaviors and activity patterns of the vulnerable population using smart card data: An activity space-based approach. *Journal of Transport Geography, 90*. https://doi.org/10.1016/j.jtrangeo.2020.102938.

Zheng, R., Xu, Y., Wang, W., Ning, G., & Bi, Y. (2020). Spatial transmission of covid-19 via public and private transportation in China. *Travel Medicine and Infectious Disease, 34, 101626–101626.* https://doi.org/10.1016/j.tmaid.2020.101626.

Zubair, H., Karoonsoontawong, A. & Kanitpong, K. (2022) Effects of COVID-19 on Travel Behavior and Mode Choice: A Case Study for the Bangkok Metropolitan Area. *Sustainability, 14, 9326.* https://doi.org/10.3390/su14159326.

Appendix

Appendix A. Descriptive statistics of Sample A

Table A-1. Socioeconomic and demographic characteristics of Sample A

	2019	2020
Standardized disposable income (from low to high) (*IC*)		
First 20%	4309 (11.42%)	4418 (11.17%)
Second 20%	6009 (15.92%)	6132 (15.51%)
Third 20%	7100 (18.81%)	7394 (18.7%)
Fourth 20%	9069 (24.03%)	9593 (24.26%)
Top 20%	11255 (29.82%)	12000 (30.35%)
Urbanization class of the home municipality (Area address density/km^2) (*U*)		
U1/Most strongly urbanized (≥2500)	10648 (28.21%)	11288 (28.55%)
U2/Highly urbanized (1500~2500)	11193 (29.66%)	11976 (30.29%)
U3/Moderately urbanized (1000~1500)	5969 (15.82%)	6341 (16.04%)
U4/Little urbanized (<1000)	9932 (26.32%)	9932 (25.12%)
Month group (*MG*)		
Jan-Feb (MA)	6397 (16.95%)	7129 (18.03%)
Mar (MB)	3201 (8.48%)	2994 (7.57%)
Apr-May (MC)	5848 (15.49%)	6945 (17.57%)
Jun-Aug (MD)	8704 (23.06%)	9681 (24.49%)
Sep (ME)	3160 (8.37%)	3236 (8.18%)
Oct-Dec (MF)	10432 (27.64%)	9552 (24.16%)
Age		
18-29	6731 (17.83%)	7291 (18.44%)
30-44	8845 (23.44%)	9416 (23.82%)
45-59	10613 (28.12%)	10767 (27.23%)
60-74	8166 (21.64%)	8443 (21.35%)
≥75	3387 (8.97%)	3620 (9.16%)
Gender (*SEX*)		
Female	18336 (48.58%)	19663 (49.73%)
Male	19406 (51.42%)	19874 (50.27%)
Ethnicity/Immigration background (*IB*)		
Dutch	30422 (80.61%)	31543 (79.78%)
Western background	3663 (9.71%)	3966 (10.03%)
Non-western background	3657 (9.69%)	4028 (10.19%)
Social participation (*SP*)		
Full-time workers (at least 30 hours per week)	16953 (44.92%)	17726 (44.83%)
Part-time workers (12-30 hours per week)	5717 (15.15%)	6194 (15.67%)
Students	2706 (7.17%)	2778 (7.03%)
Retires/VUT	7463 (19.77%)	7888 (19.95%)
Unemployed, incapacitated, household, or others	4903 (12.99%)	4951 (12.52%)
Education attainment (*EDU*)		

No or primary education	1371 (3.63%)	1186 (3%)
Lower vocational education	6215 (16.47%)	6070 (15.35%)
Secondary vocational education	12664 (33.55%)	12872 (32.56%)
Higher vocational education & university	16579 (43.93%)	18383 (46.5%)
Other training	913 (2.42%)	1026 (2.6%)
Number of household members (*HM*)		
1	7110 (18.84%)	7642 (19.33%)
2	15074 (39.94%)	15675 (39.65%)
3	5835 (15.46%)	6000 (15.18%)
4	6908 (18.3%)	7290 (18.44%)
≥5	2815 (7.46%)	2930 (7.41%)
Household composition (*HS*)		
Couple with children	14492 (38.4%)	15110 (38.22%)
Single-person household and others	7304 (19.35%)	7876 (19.92%)
Couple without children	13977 (37.03%)	14564 (36.84%)
Single-parent household (and children)	1969 (5.22%)	1987 (5.03%)
Household car ownership (*AUTO*)		
0 car	5489 (14.54%)	5771 (14.6%)
1 car	18484 (48.97%)	19192 (48.54%)
2 cars	10646 (28.21%)	11290 (28.56%)
>=3 cars	3123 (8.27%)	3284 (8.31%)
The respondent holding a driving license (*DL*)		
No	4662 (12.35%)	4805 (12.15%)
Yes	33080 (87.65%)	34732 (87.85%)
Weekday (*WD*)		
Sunday	5078 (13.45%)	5133 (12.98%)
Monday	5473 (14.5%)	5489 (13.88%)
Tuesday	5606 (14.85%)	5774 (14.6%)
Wednesday	5340 (14.15%)	5545 (14.02%)
Thursday	5439 (14.41%)	5810 (14.7%)
Friday	5557 (14.72%)	5952 (15.05%)
Saturday	5249 (13.91%)	5834 (14.76%)
Bank holiday (*FD*)		
No	37045 (98.15%)	38653 (97.76%)
Yes	697 (1.85%)	884 (2.24%)
NUTS-1 Region* of residence (*Regio*)		
North Netherlands	3161 (8.38%)	3024 (7.65%)
East Netherlands	7380 (19.55%)	6944 (17.56%)
West Netherlands	20057 (53.14%)	22123 (55.96%)
South Netherlands	7144 (18.93%)	7446 (18.83%)

* For statistical purpose, the Netherlands is divided into four regions at the first level, namely North, East, West, and South Netherlands. Each region includes these following provinces:

North – Groningen, Friesland, and Drenthe. East – Overijssel, Flevoland, and Gelderland.

South – North-Brabant, and Limburg. West – North-Holland, South-Holland, Utrecht, Zeeland.

Appendix B. General changes of travel distance, time, and probability (Multiple tables)

1. General patterns

Table B-1. Changes of average travel distance, travel time, and travel probability* per travel purpose between 2019 and 2020

		Work						Leisure						Shopping						Visit/stay					
Month-groups		A	B	C	D	E	F	A	B	C	D	E	F	A	B	C	D	E	F	A	B	C	D	E	F
Distance/km	2019	21.39	20.22	21.28	19.68	22.27	22.01	8.27	9.94	10.75	12.31	11.79	9.55	4.14	4.37	3.96	3.97	3.51	4.32	7.88	6.94	7.60	8.95	8.30	7.73
	2020	20.20	16.62	8.82	11.24	14.59	11.65	8.35	6.70	7.60	10.04	9.57	6.02	3.97	3.41	3.18	4.29	3.61	3.56	6.60	4.69	4.38	7.34	5.80	5.24
	Diff	-5.55%	-17.78%	-58.53%	-42.92%	-34.50%	-47.05%	0.89%	-32.63%	-29.25%	-18.44%	-18.83%	-37.02%	-4.23%	-22.15%	-19.79%	7.96%	3.04%	-17.63%	-16.21%	-32.45%	-42.40%	-18.00%	-30.07%	-32.25%
Time/min	2019	31.81	30.71	31.60	28.20	33.62	32.40	27.74	30.01	35.33	38.67	36.06	29.45	10.90	11.25	10.86	11.15	10.06	11.15	10.26	9.80	10.45	12.23	10.62	10.38
	2020	30.53	24.34	13.14	17.03	21.23	17.36	28.48	33.66	46.14	42.06	38.96	33.85	11.23	10.50	10.00	11.84	10.90	10.41	9.40	6.74	6.34	10.55	8.73	7.55
	Diff	-4.02%	-20.76%	-58.42%	-39.63%	-36.84%	-46.41%	2.65%	12.18%	30.60%	8.77%	8.05%	14.93%	2.99%	-6.72%	-7.89%	6.23%	8.36%	-6.65%	-8.38%	-31.21%	-39.33%	-13.72%	-17.82%	-27.25%
Probability	2019	0.391	0.397	0.400	0.348	0.398	0.386	0.353	0.360	0.378	0.369	0.362	0.355	0.285	0.289	0.280	0.286	0.263	0.285	0.153	0.146	0.154	0.157	0.140	0.154
	2020	0.373	0.273	0.175	0.226	0.283	0.228	0.369	0.325	0.359	0.379	0.386	0.339	0.300	0.264	0.250	0.298	0.284	0.279	0.152	0.096	0.090	0.146	0.132	0.114
	Diff	-4.67%	-31.14%	-56.22%	-34.95%	-29.05%	-40.97%	4.76%	-9.67%	-4.93%	2.65%	6.73%	-4.32%	5.17%	-8.67%	-10.58%	4.22%	7.90%	-2.10%	-0.41%	-34.42%	-41.67%	-7.23%	-5.04%	-26.07%

* Definition of "travel probability" see section 4.3.

Specifically, the magnitude of changes is shown in Table B-2.

Table B-2. Magnitude of change of average travel distance, travel time, and travel probability* per month-group between 2019 and 2020.

	Work	Leisure	Shopping	Visit	Work	Leisure	Shopping	Visit	Work	Leisure	Shopping	Visit
Month group	A (Jan – Feb)				B (March)				C (Apr – May)			
Distance	-5.55%	**0.89%**	-4.23%	-16.21%	-17.78%	-32.63%	-22.15%	-32.45%	-58.53%	-29.25%	-19.79%	-42.40%
Time	-4.02%	**2.65%**	**2.99%**	-8.38%	-20.76%	**12.18%**	-6.72%	-31.21%	-58.42%	**30.60%**	-7.89%	-39.33%
Probability	-4.67%	**4.76%**	**5.17%**	-0.41%	-31.14%	-9.67%	-8.67%	-34.42%	-56.22%	-4.93%	-10.58%	-41.67%
Month group	D (Jun – Aug)				E (September)				F (Oct – Dec)			
Distance	-42.92%	-18.44%	**7.96%**	-18.00%	-34.50%	-18.83%	**3.04%**	-30.07%	-47.05%	-37.02%	-17.63%	-32.25%
Time	-39.63%	**8.77%**	**6.23%**	-13.72%	-36.84%	**8.05%**	**8.36%**	-17.82%	-46.41%	**14.93%**	-6.65%	-27.25%
Probability	-34.95%	**2.65%**	**4.22%**	-7.23%	-29.05%	**6.73%**	**7.90%**	-5.04%	-40.97%	-4.32%	-2.10%	-26.07%

It can be concluded that a sharp decrease appeared since March and gaps between 2019 and 2020 were still remarkable in the next nine months.

2. Variations with income levels

Table B-3. Changes of average travel distance, travel time, and travel probability* per travel purpose & per income class between 2019 and 2020.

Note: **Max.** and **Min**. of percentages during the pandemic are marked with **bold** formats. Negative Diff/% are marked with red colours.

			A	B	C	D	E	F		A	B	C	D	E	F
		Income class	Work						Income class	Leisure					
Distance/km	2019	Low	12.10	10.35	13.77	10.86	13.91	14.60	Low	8.08	7.88	9.22	9.97	8.55	7.09
		Middle	19.65	16.98	18.42	17.32	19.56	18.76	Middle	7.10	9.17	10.18	11.71	11.34	9.16
		High	27.19	27.47	27.52	25.80	28.14	27.95	High	9.44	11.53	12.00	13.89	13.51	10.91

	2020	Low	10.33	7.74	4.58	5.85	10.40	7.61	Low	6.58	7.05	6.67	7.53	7.97	4.79
		Middle	16.90	16.58	8.42	10.59	13.80	11.43	Middle	7.59	6.21	7.55	9.55	9.47	5.41
		High	27.47	20.29	10.92	14.09	16.99	13.57	High	9.79	6.98	8.03	11.53	10.31	7.07
	Diff /%	Low	-14.69	-25.24	-66.77	-46.19	-25.23	-47.90	Low	-18.53	-10.51	-27.65	-24.41	-6.86	-32.40
		Middle	-13.97	-2.34	-54.26	-38.85	-29.48	-39.09	Middle	6.90%	-32.29	-25.83	-18.43	-16.49	-40.93
		High	1.03	-26.14	-60.33	-45.38	-39.62	-51.45	High	3.66%	-39.45	-33.09	-17.03	-23.70	-35.16
Time/min	2019	Low	22.13	19.95	25.08	19.52	26.31	24.89	Low	32.25	30.21	39.36	41.26	37.31	27.93
		Middle	30.29	27.06	29.13	26.00	30.05	28.53	Middle	25.56	30.49	32.80	38.23	35.51	29.69
		High	37.60	38.73	37.01	34.11	39.84	38.94	High	27.74	29.51	35.75	37.95	36.06	29.86
	2020	Low	21.07	17.04	9.84	11.81	17.41	14.59	Low	30.07	35.11	45.22	42.22	36.13	34.28
		Middle	27.64	23.93	12.56	17.10	20.56	17.63	Middle	27.39	33.84	45.65	41.36	37.23	33.09
		High	37.27	27.68	15.02	19.15	23.37	18.29	High	28.74	32.92	46.97	42.63	41.64	34.35
	Diff /%	Low	-4.79	-14.60	-60.78	-39.51	-33.83	-41.37	Low	-6.74	16.22	14.90	2.33	**-3.16**	**22.74**
		Middle	-8.73	-11.54	-56.90	-34.21	-31.58	-38.19	Middle	7.15	11.01	**39.20**	8.19	**4.86**	11.43
		High	-0.88	-28.53	-59.42	-43.85	-41.33	-53.02	High	3.62	11.53	**31.39**	**12.34**	15.47	15.02
Probability	2019	Low	0.269	0.269	0.303	0.237	0.281	0.283	Low	0.329	0.299	0.340	0.335	0.306	0.293
		Middle	0.382	0.373	0.382	0.342	0.389	0.360	Middle	0.335	0.364	0.357	0.360	0.363	0.350
		High	0.466	0.489	0.472	0.410	0.465	0.462	High	0.383	0.390	0.419	0.395	0.388	0.389
	2020	Low	0.247	0.180	0.104	0.148	0.204	0.165	Low	0.311	0.268	0.282	0.300	0.307	0.269
		Middle	0.353	0.273	0.185	0.229	0.292	0.241	Middle	0.355	0.319	0.357	0.364	0.382	0.336
		High	0.461	0.324	0.204	0.266	0.314	0.249	High	0.415	0.363	0.404	0.435	0.432	0.379
	Diff /%	Low	-8.13	-33.05	**-65.72**	-37.63	**-27.30**	-41.60	Low	-5.44%	-10.62	**-17.22**	-10.54	**0.19**	-7.95
		Middle	-7.70	-26.82	**-51.40**	-33.04	**-24.89**	-32.96	Middle	6.11	**-12.24**	0.04	1.06	**5.09**	-4.20
		High	-1.14	-33.86	**-56.70**	-35.28	**-32.53**	-46.17	High	8.25	**-7.15**	-3.61	10.32	**11.14**	-2.37

			A	B	C	D	E	F		A	B	C	D	E	F
		Income class	Shopping						Income class	Visit/Stay					
Distance/km	2019	Low	4.31	3.85	2.86	4.56	2.58	3.15	Low	6.80	5.55	7.36	8.76	7.49	8.71
		Middle	4.17	4.88	4.19	4.03	3.41	4.64	Middle	6.65	7.33	7.47	8.69	7.94	6.99
		High	4.05	4.19	4.28	3.66	3.97	4.51	High	9.50	7.25	7.85	9.28	8.95	8.00
	2020	Low	3.31	3.14	2.71	4.27	2.75	3.05	Low	6.17	5.56	4.09	6.42	6.76	5.33
		Middle	4.26	3.67	3.07	4.31	3.64	3.76	Middle	6.20	4.74	4.25	6.76	4.71	3.76
		High	4.00	3.28	3.47	4.28	3.94	3.60	High	7.15	4.29	4.61	8.25	6.38	6.51
	Diff /%	Low	-23.16	**-18.48**	-5.41	-6.26	**6.59**	-3.28	Low	-9.29	**0.17**	**-44.44**	-26.64	-9.84	-38.83
		Middle	2.18	-24.68	**-26.75**	**6.81**	6.77	-19.01	Middle	-6.80	-35.32	-43.03	**-22.25**	-40.70	**-46.18**
		High	-1.13	**-21.73**	-18.92	**16.96**	-0.76	-20.23	High	-24.80	-40.83	**-41.22**	**-11.08**	-28.71	-18.56
Time/min	2019	Low	13.43	13.13	11.95	14.09	11.89	11.86	Low	10.10	10.37	12.24	13.16	12.70	12.52
		Middle	10.58	11.93	11.25	11.05	9.94	11.78	Middle	9.39	10.26	9.91	11.85	9.89	9.87
		High	10.05	9.82	9.97	9.96	9.42	10.30	High	11.15	9.15	10.09	12.19	10.45	9.96
	2020	Low	13.79	11.56	11.00	13.51	12.79	11.69	Low	10.56	7.65	6.51	10.42	11.33	8.67
		Middle	11.76	11.05	10.00	12.21	10.64	10.52	Middle	8.99	7.16	6.51	10.03	7.18	6.07
		High	9.62	9.57	9.59	10.81	10.36	9.77	High	9.26	6.00	6.11	11.08	9.04	8.40
	Diff /%	Low	2.66	**-11.98**	-7.97	-4.13	**7.55**	-1.39	Low	4.53%	-26.23	**-46.82**	-20.83	**-10.79**	-30.71
		Middle	11.19	-7.40	**-11.11**	**10.50**	7.00	-10.69	Middle	-4.25	-30.18	-34.26	**-15.32**	-27.41	**-38.55**
		High	-4.32	-2.50	-3.75	8.58	**9.95**	**-5.16**	High	-16.94	-34.45	**-39.41**	**-9.06**	-13.56	-15.72
Probability	2019	Low	0.300	0.296	0.279	0.298	0.249	0.272	Low	0.135	0.141	0.154	0.142	0.138	0.155
		Middle	0.286	0.290	0.279	0.291	0.259	0.294	Middle	0.155	0.149	0.151	0.158	0.139	0.150
		High	0.276	0.286	0.280	0.273	0.273	0.282	High	0.161	0.147	0.156	0.165	0.140	0.156
	2020	Low	0.300	0.244	0.214	0.268	0.281	0.274	Low	0.132	0.081	0.073	0.126	0.113	0.104
		Middle	0.313	0.266	0.254	0.310	0.283	0.279	Middle	0.155	0.099	0.093	0.141	0.133	0.107

		High	0.288	0.274	0.266	0.301	0.286	0.281		High	0.161	0.101	0.095	0.162	0.142	0.125
	Diff /%	Low	-0.14	-17.61	**-23.12**	-10.00	**12.80**	0.62		Low	-2.05	-42.30	**-52.31**	**-11.38**	-18.02	-32.99
		Middle	9.21	-8.19	**-9.00**	6.52	**8.96**	-5.08		Middle	-0.46	-33.62	**-38.21**	-10.74	**-4.92**	-28.53
		High	4.28	-4.18	**-5.21**	**10.12**	4.7	-0.35		High	0.49	-31.22	**-39.15**	-1.78	**1.38**	-20.26

3. Variations with urbanization classes

Table A-4. Changes of average travel distance, travel time, and travel probability* per travel purpose & per urbanity level between 2019 and 2020.

Note1: **Max.** and **Min**. during the pandemic are marked with **bold** formats. Negative Diff/% are marked with red colours.

Note2: Urban-rural continuum, classified as **Level 4 to 1**, from the ***least*** urbanized to the ***most strongly*** urbanized. See Section 4.3.3.

			A	B	C	D	E	F		A	B	C	D	E	F
		Urbanity level	Work						Urbanity level	Leisure					
Distance/km	2019	U4	23.27	19.42	24.29	20.19	24.63	25.02	U4	8.08	10.08	10.82	13.73	15.07	10.21
		U3	22.28	16.98	10.23	14.35	17.86	13.62	U3	9.80	8.07	7.86	10.03	10.16	6.64
		U2	23.87	21.88	21.46	19.57	20.30	22.14	U2	8.75	10.44	9.62	13.10	12.16	10.52
		U1	20.34	16.51	10.18	11.29	13.61	13.42	U1	8.75	5.76	7.11	10.55	10.98	6.27
	2020	U4	21.51	20.81	20.85	19.96	22.88	22.01	U4	8.41	10.49	11.52	12.25	11.99	10.09
		U3	21.25	17.17	9.14	10.66	16.68	12.11	U3	7.62	6.60	7.67	10.01	8.81	5.93
		U2	18.20	19.48	18.89	18.97	20.65	19.00	U2	8.03	9.01	10.51	10.54	8.57	7.78
		U1	17.30	15.75	6.45	9.13	9.99	8.41	U1	7.69	6.07	7.59	9.78	9.01	5.40
	Diff /%	U4	-4.25	**-12.58**	**-57.87**	-28.95	-27.47	-45.56	U4	21.19	**-20.01**	-27.34	-26.97	-32.57	**-34.92**
		U3	-14.77	**-24.55**	**-52.55**	-42.32	-32.96	-39.39	U3	0.06	**-44.85**	-26.15	-19.49	**-9.68%**	-40.40
		U2	-1.20	**-17.50**	**-56.14**	-46.60	-27.11	-44.98	U2	-9.49	-37.10	-33.44	**-18.23**	-26.52	**-41.19**
		U1	-4.98%	**-19.19**	**-65.86**	-51.86	-51.60	-55.72	U1	-4.30	**-32.65**	-27.77	-7.20%	**5.08%**	-30.61

Time/min	2019	U4	29.83	26.18	32.60	25.33	33.96	32.54	U4	27.26	30.76	33.40	39.56	35.73	29.17
		U3	29.67	22.55	14.65	19.80	23.55	18.68	U3	31.40	34.89	44.92	40.99	36.97	34.10
		U2	32.26	32.35	30.49	27.22	31.35	31.24	U2	28.22	26.03	33.37	41.25	38.44	30.81
		U1	29.09	22.83	14.13	16.65	19.23	18.59	U1	28.31	32.13	43.81	42.51	38.31	34.03
	2020	U4	32.77	31.07	31.23	28.23	32.44	32.19	U4	26.63	30.62	37.48	37.61	34.62	28.98
		U3	31.34	26.11	12.81	15.99	23.85	17.35	U3	27.17	32.85	45.35	40.72	38.20	34.15
		U2	32.36	33.63	31.71	31.51	35.70	33.13	U2	29.07	30.84	35.96	37.44	36.58	29.48
		U1	31.17	24.94	11.56	15.95	17.55	15.50	U1	27.50	34.31	49.41	44.17	41.96	33.19
	Diff /%	U4	-0.55	**-13.86**	**-55.06**	-21.81	-30.64	-42.59	U4	15.17	13.44	**34.46**	3.62	**3.46**	16.93
		U3	-9.82	**-29.42**	**-53.67**	-38.83	-38.67	-40.49	U3	0.31	23.46	**31.31**	3.05	**-0.32**	10.45
		U2	-4.35	**-15.95**	**-58.98**	-43.38	-26.48	-46.11	U2	2.06	**7.27**	**21.01**	8.26	10.33	17.84
		U1	-3.70	**-25.83**	**-63.54**	-49.39	-50.85	-53.20	U1	-5.40	**11.26**	**37.41**	17.96	14.71	12.61
Probability	2019	U4	0.369	0.371	0.401	0.332	0.407	0.385	U4	0.344	0.362	0.360	0.370	0.351	0.369
		U3	0.351	0.277	0.201	0.246	0.310	0.252	U3	0.375	0.356	0.362	0.372	0.376	0.359
		U2	0.401	0.410	0.393	0.327	0.391	0.382	U2	0.362	0.337	0.374	0.383	0.377	0.368
		U1	0.378	0.298	0.193	0.256	0.289	0.244	U1	0.364	0.338	0.377	0.410	0.403	0.346
	2020	U4	0.398	0.391	0.394	0.343	0.368	0.380	U4	0.345	0.383	0.392	0.357	0.352	0.348
		U3	0.368	0.289	0.168	0.221	0.300	0.228	U3	0.372	0.326	0.359	0.380	0.377	0.336
		U2	0.400	0.421	0.408	0.381	0.425	0.398	U2	0.363	0.348	0.380	0.372	0.374	0.340
		U1	0.395	0.240	0.149	0.199	0.236	0.198	U1	0.365	0.292	0.347	0.366	0.396	0.323
	Diff /%	U4	-4.93	-25.25	**-49.80**	-25.82	**-23.93**	-34.50	U4	9.01	-1.77	0.60	0.47	**7.22**	**-2.77**
		U3	-5.88	-27.28	**-50.98**	**-21.58**	-25.95	-36.10	U3	0.55	0.31	0.72	**6.99**	6.87	**-6.19**
		U2	-7.57	-25.92	**-57.32**	-35.58	**-18.55**	-39.91	U2	7.74	**-15.07**	-8.57	6.44	**7.13**	-3.39
		U1	-1.20	**-43.04**	**-63.40**	-47.75	-44.50	-50.10	U1	0.45	**-16.12**	-8.85	-1.48	**5.93**	-5.25

			A	B	C	D	E	F		A	B	C	D	E	F
		Income class	Shopping						Income class	Visit/Stay					
Distance/km	2019	U4	5.02	5.38	4.87	4.50	4.45	5.13	U4	8.18	6.40	7.67	9.17	8.74	7.15
		U3	5.06	4.09	4.02	5.22	4.28	4.48	U3	6.34	5.16	4.78	6.67	5.61	5.17
		U2	4.35	5.64	3.85	3.95	3.03	4.81	U2	7.31	5.90	7.92	9.28	6.19	7.60
		U1	3.77	3.88	3.02	4.60	3.09	3.56	U1	6.49	4.71	3.89	7.46	4.61	4.41
	2020	U4	4.24	3.90	3.66	4.27	3.97	4.37	U4	7.21	8.35	8.00	9.01	10.13	8.16
		U3	4.16	2.85	3.06	4.04	3.66	3.26	U3	6.93	4.37	3.69	6.87	5.19	5.41
		U2	3.15	3.25	3.53	3.15	2.47	3.21	U2	8.61	6.62	6.93	8.49	7.14	7.92
		U1	2.96	3.10	2.65	3.57	3.27	3.06	U1	6.52	4.59	5.02	8.35	7.30	5.58
	Diff /%	U4	0.84	**-23.98**	-17.52	**15.90**	-3.95	-12.67	U4	-22.47	**-19.41**	**-37.74**	-27.24	-35.88	-27.64
		U3	-13.16	**-31.25**	-21.47	**16.44**	1.84	-26.14	U3	-11.21	-20.15	**-50.85**	**-19.60**	-25.48	-41.91
		U2	-1.87	**-26.87**	-16.35	**-5.51**	-7.84	-25.25	U2	-3.77	-47.59	**-53.87**	**-23.70**	-48.81	-33.71
		U1	-5.80	-4.71	**-24.98**	13.41	**32.06**	-4.60	U1	-24.24	**-30.75**	-27.64	-1.67	**2.24**	-29.55
Time/min	2019	U4	10.51	10.61	10.16	10.57	8.56	10.31	U4	10.02	8.38	10.20	12.13	10.58	9.76
		U3	10.65	10.21	9.64	11.26	10.41	9.53	U3	8.85	6.86	6.30	9.71	8.26	6.91
		U2	10.15	11.81	9.83	10.42	8.91	11.46	U2	9.72	9.02	10.31	12.18	8.43	9.59
		U1	9.76	11.53	9.24	11.57	9.38	9.88	U1	9.25	6.94	6.12	10.98	7.24	6.70
	2020	U4	10.91	11.79	10.84	11.82	11.34	11.54	U4	9.73	10.75	10.06	12.13	12.46	10.70
		U3	11.63	10.23	9.85	11.74	11.08	10.27	U3	9.29	6.08	5.51	9.49	7.57	7.44
		U2	11.66	11.02	12.09	11.41	10.64	11.38	U2	11.32	10.58	11.16	12.47	9.91	11.08
		U1	12.05	10.45	10.92	12.61	12.03	11.64	U1	10.06	7.25	7.38	12.19	11.20	8.71
	Diff /%	U4	1.36%	-3.77%	-5.14%	6.49%	**21.61%**	**-7.52%**	U4	-11.60	**-18.18**	**-38.28**	-19.99	-21.95	-29.17
		U3	-3.84%	-2.37%	-6.07%	**11.02%**	5.24%	**-13.77%**	U3	-4.89	-23.02	**-40.66**	**-9.88**	-14.08	-30.12
		U2	6.61%	**-13.23%**	-9.15%	**-0.66%**	-2.27%	-11.00%	U2	-4.57	-43.45	**-45.29**	**-21.77**	-39.23	-30.46
		U1	3.41%	-5.14%	**-9.68%**	10.56%	**13.05%**	2.26%	U1	-11.20	-31.47	**-33.91**	-2.27%	**12.98%**	-21.35

Probability	2019	U4	0.259	0.281	0.260	0.269	0.234	0.266	U4	0.165	0.153	0.158	0.171	0.157	0.162
		U3	0.272	0.262	0.234	0.282	0.278	0.257	U3	0.160	0.111	0.092	0.151	0.148	0.124
		U2	0.278	0.282	0.277	0.282	0.268	0.289	U2	0.162	0.135	0.158	0.163	0.140	0.156
		U1	0.292	0.279	0.252	0.303	0.262	0.281	U1	0.163	0.099	0.107	0.157	0.136	0.113
	2020	U4	0.290	0.312	0.292	0.297	0.281	0.293	U4	0.150	0.156	0.145	0.155	0.145	0.153
		U3	0.315	0.269	0.254	0.304	0.277	0.288	U3	0.151	0.091	0.086	0.138	0.117	0.108
		U2	0.308	0.278	0.286	0.291	0.267	0.292	U2	0.140	0.137	0.157	0.144	0.119	0.145
		U1	0.312	0.254	0.259	0.301	0.307	0.287	U1	0.142	0.087	0.082	0.144	0.133	0.111
	Diff /%	U4	4.99	-7.02	**-9.99**	4.66	**19.04**	-3.32	U4	-2.98	-27.60	**-41.76**	-11.72	**-5.23**	-23.79
		U3	5.10	-1.14	**-8.87**	**7.44**	-2.16	-2.82	U3	0.50%	-26.45	**-32.20**	-3.45	**-2.55**	-27.35
		U2	8.61	**-13.99**	-13.13	**2.27**	-1.45	-1.76	U2	0.52	**-41.67**	-40.52	**-10.63**	-19.37	-29.21
		U1	1.22	-8.60	**-9.62**	3.62	**15.07**	-1.74	U1	1.34	-36.70	**-47.82**	0.10	**11.29**	-23.53

Appendix C. Cross-tabulation of urbanization levels and Dutch municipalities.

Table C-1. Number of municipalities and respondents in each urbanization class (Sample B, Year = 2020)

Urbanity Level	U1	U2	U3	U4
Num. of municipalities	21	74	76	184
Num. of respondents	15547	16170	8397	13386

Note: according to section 4.3.3, the urbanization class (urbanity level) is defined as average address density.

The address density is determined with a radius of 1km around that address. A density value is derived for each municipality by calculating the average address density for all addresses within that municipality. Thus, the urbanity level in the data was depended on the municipality where the respondent lived/registered.

Level 1 (U1). Most strongly urbanized (≥2500 addresses per km2).

Level 2 (U2). Highly urbanized (1500~2500).

Level 3 (U3). Moderately urbanized (1000~1500).

Level 4 (U4). Little urbanized (<1000).

The following table shows that only 5 out of 12 provinces in the Netherlands contain cities at the top urbanity level, among which South-Holland has the largest number, making up more than half in this country.

Table C-2. Number of cities in each province (as of 2020) *

Prov./Urban. Level	U1	U2	U3	U4	Sum
1 Groningen	1	0	2	9	*12*
2 Friesland	0	1	3	14	*18*
3 Drenthe	0	1	2	9	*12*
4 Overijssel	0	5	5	15	*25*
5 Flevoland	0	1	2	3	*6*
6 Gelderland	0	7	10	34	*51*
7 Utrecht	1	7	7	11	*26*
8 North-Holland	6	14	14	13	*47*
9 South-Holland	11	22	9	10	*52*
10 Zeeland	0	2	1	10	*13*
11 North-Brabant	2	8	16	36	*62*
12 Limburg	0	6	5	20	*31*

* Municipalities in the Netherlands have been merging by a bottom-up process for many years. As of 2020, the number of municipalities in the nation is 355. (The same as that of 2019.)

The number of respondents in each urbanity level of every province are shown as follows.

Table C-3. Number of respondents in each province – urbanity-level unit (Sample B, Year = 2020)

Prov./Urban Class	U1	U2	U3	U4	Sum
1 Groningen	669	0	75	727	*1471*
2 Friesland	0	318	287	875	*1480*
3 Drenthe	0	167	200	788	*1155*
4 Overijssel	0	1335	406	1045	*2786*
5 Flevoland	0	568	411	396	*1375*
6 Gelderland	0	1973	853	2299	*5125*
7 Utrecht	1967	2474	1537	1207	*7185*
8 North-Holland	3345	2890	851	975	*8061*
9 South-Holland	8409	2983	1590	970	*13952*
10 Zeeland	0	229	92	610	*931*
11 North-Brabant	1157	1804	1402	2081	*6444*
12 Limburg	0	1429	693	1413	*3535*
Sum	*15547*	*16170*	*8397*	*13386*	***53500***

Table C-4. Number of respondents in each province – urbanity-level unit (Sample A, Year = 2020)

Prov./Urban Class	U1	U2	U3	U4	Sum
1 Groningen	515	0	52	491	*1058*
2 Friesland	0	238	214	656	*1108*
3 Drenthe	0	132	140	586	*858*
4 Overijssel	0	996	308	791	*2095*
5 Flevoland	0	395	300	285	*980*
6 Gelderland	0	1513	629	1727	*3869*
7 Utrecht	1528	1881	1179	888	*5476*
8 North-Holland	2413	2103	649	723	*5888*
9 South-Holland	5944	2176	1211	724	*10055*
10 Zeeland	0	180	74	450	*704*
11 North-Brabant	888	1356	1090	1569	*4903*
12 Limburg	0	1006	495	1042	*2543*
Sum	*11288*	*11976*	*6341*	*9932*	***39537***