Working from home: Should we stimulate it for transport reasons?

Analysis of travel behaviour during COVID-19 in the Netherlands

Jil Brimaire

TU Delft

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by

Jil Brimaire

to obtain the degree of Master of Science
in Complex Systems Engineering and Management (CoSEM)
Faculty of Technology, Policy and Management
at the Delft University of Technology,
to be defended publicly on Thursday August 25, 2022

Student number:	5295602	
Project duration:	April 7, 2022 – August 25, 2022	
Thesis committee:	Dr. ir. M. Kroesen,	TU Delft, chair
	Dr. B. Pudane,	TU Delft, first supervisor
	Dr. ir. C. van Daalen,	TU Delft, second supervisor
	Ir. M.C. de Haas,	Kennisinstituut voor Mobiliteitsbeleid, external supervisor
	Ir. R. Faber,	Kennisinstituut voor Mobiliteitsbeleid, external supervisor

Preface

Describing the process leading up to this thesis in three phases, I would say my company supervisors summarised it perfectly: The beginning is hard because you do not really know what you will do, the middle part is tough because you are confused all the time, and the end is challenging because you are getting tired after the long journey (A supervisor meeting with Roel & Mathijs, June 2022). Being at the end of this journey, I must agree. The past six months during which I worked on this document mark a journey filled with ups and downs, euphoria and confusion, laughter and tears. Ultimately, every step was essential in paving the way for the document you are looking at. Reflecting on my work, I am incredibly proud of the end result I delivered and the process that got me there. However, this journey would not have been the same without the incredible people who supported me. I use the following paragraphs to briefly express my gratitude to the people who have been most involved in the past six months.

First of all, I want to thank my graduation committee from TU Delft. Baiba Pudane, thank you for being an initiator of this project alongside me. Thank you for helping me find and shape a topic, gathering fantastic committee members and pointing out an internship possibility at the KiM. Your dynamism motivated me from the beginning, especially to believe in my own skills. During the process, your critical thoughts certainly kept me busy, but these pushed my work to greater quality. Maarten Kroesen, as my chair, it was probably not self-evident that we met for bi-weekly meetings. Thank you for this kind and regular guidance. You pushed me to take decisions and deliver written documents every once in a while. These little sprints were undoubtedly needed. Lastly, you helped me think simpler and acknowledge that this project is ’just’ a master thesis. Finally, Els van Daalen, we only met at official meetings. However, thanks to your feedback from a different perspective, I improved my overall work after each time we met. Next, I want to thank my two supervisors from the KiM, Roel Faber and Mathijs De Haas. Thank you for taking the time for very flexible meetings whenever I asked for feedback or when I was running into problems with the MPN data or my analyses. Your kind advice, support and patience helped me overcome multiple frustrations.

Finally, this project would not have ended as well as it did without the support of my dear family and friends. Thank you for the immeasurable support on this journey, for distracting or motivating me when needed and for listening to me repeatedly. I am sure you all learned a thing or two about WFH and travel behaviour in the past months.

Looking back, I am surprised that the time was more enjoyable than expected. For now, I am more than ready for a long overdue break and excited for what the future holds.

Jil Brimaire
Delft, August 2022

Summary

The Dutch Ministry of Infrastructure and Water Management is committed to enhancing the accessibility and sustainability of the Dutch mobility system. Working from home (WFH) has been discussed as a policy lever to decrease commute travel and, thereby, congestion for decades. During the COVID-19 pandemic, this discussion regained momentum. WFH was a key factor for the decrease in commute travel by public transport and car in the Netherlands, which decreased congestion. While congestion is detrimental to the environment, congestion also challenges the accessibility of economic centres. Against this background, the Ministry wants to stimulate WFH post-pandemic to retain some of the sustainability and accessibility benefits identified during the pandemic. WFH can enhance the accessibility of the mobility system thanks to reduced commute trips during peak hours. However, WFH may not necessarily lead to a reduction in travel. On the contrary, other non-work trips may compensate for reduced commute trips. Besides this, the pandemic showed severe consequences for mode use. Many people who adopted working from home commuted by public transport (PT) prior to the pandemic, and the use of individual modes was encouraged, which may again challenge the accessibility of the mobility system but also the sustainability of travel patterns. This situation presents a complex context for assessing the benefits of WFH for the transport system.

Although the stimulation of WFH may be a policy lever to increase the accessibility of the mobility system, the full effect of WFH on overall personal mobility is unknown. Studying pre-, during- and post-COVID-19 measures data, this study assesses the impact of a change in WFH on activity-travel patterns. The main research question is as follows:

How did changes in WFH influence activity-travel patterns during the pandemic in the Netherlands?

Based on a literature review, a theoretically and contextually grounded conceptual model is set up. The building blocks of this conceptual model, shown in Figure 1, are a change in WFH, commute travel, other non-work travel, modes, individual characteristics and COVID-19 measures. Commute travel, non-work travel and mode use together define **activity-travel patterns**. The conceptual model synthesizes three important relationships from literature. First, WFH impacts travel for different purposes: commute and non-work travel (1). Next, the relationship between activities, commute and non-work travel is included (2). Furthermore, an indirect relationship between WFH and mode use (3), running through activities is synthesized. For instance, WFH may reduce the use of specific modes, such as PT. However, this is due to the elimination of commutes. Relationships presented by dotted lines are not actively included in this research.

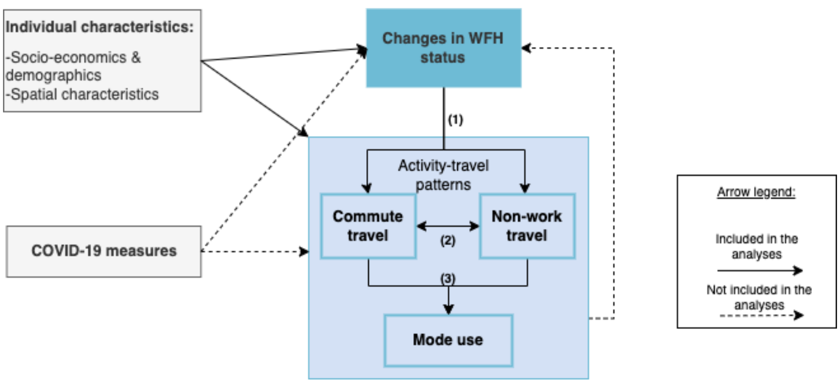

Figure 1: Conceptual Model

Data from the Netherlands Mobility Panel (MPN), collected between 2019-2022, is used to study the effect of a change in WFH on activity-travel patterns. Generally, about 2000 Dutch households form the MPN. During the pandemic, the Netherlands Institute for Transport Policy Analysis (KiM) conducted special COVID-19 measurements in addition to the yearly measurement in September-November. By this, data from different time points in the pandemic is available. 2019 data serves as a pre-COVID-19 time point, 2021 data presents the situation during COVID-19 measures, and May 2022 data gives insight about post-COVID-19 measures behaviour. The MPN includes, amongst others WFH and travel diary data. Using descriptive analyses, Latent Class Analyses and Latent Transition Analyses, this research studies transitions between activity-travel patterns after a change in WFH.

Absolute changes in the WFH hours are analysed descriptively to conclude on overall behavioural trends. As expected, many people increased their weekly WFH hours between 2019 and 2021. Almost no decreases in WFH appear for 2019-2021. For 2021-2022, decreases in WFH occur, while not many increases in WFH appear. Weighing off the observed frequency of changes in WFH against the attempted model, Latent Transition Analysis, two change in WFH variables are operationalised for two different models to keep the models parsimonious and reliable. For 2019-2021, the impact of an increase in WFH on transitions in activity-travel patterns is studied. While for 2021-2022, the impact of a decrease in WFH on transitions in activity-travel patterns is studied. For 2019-2021, decreases in WFH are merged with no change in WFH cases and vice versa for an increase in WFH for 2021-2022. Based on the distribution of the data, two levels of increases in WFH are defined: a small and a large increase in WFH. The 2021-2022 data does not allow for a similar definition of two decrease levels. For the definition of an increase and a decrease, strict intervals based on the hour counts present a limitation of this research. However, this is a limitation of the dataset as the exact number of days respondents worked from home is unavailable.

Latent Class Analysis reveals seven distinct activity-travel patterns for both wave pairs 2019-2021 and 2021-2022. Six out of seven classes remain the same for both wave pairs. The first class are car commuters, these travellers mostly take commute trips by car. The second class are car users for many other trips, namely more than 7 trips, on average over 3 days, for other purposes by car. The third class are active mode and car users for many other trips in 2019-2021. In 2021-2022, this class changes the absolute values on the indicators leading to being labelled car commuters and active mode users for other trips. The fourth class is a low mobility class, which shows hardly any trips. The fifth class are active mode commuters with mostly commute trips by active modes. The sixth class are active mode users for many other trips, counting more than 6 other trips by active modes in three days. The final class are multi-modal users who commute by public transport.

Latent Transition Analysis (LTA) allows assessing the impact of a change in WFH on transitions in activity-travel patterns. Significant effects on transitions appear for a small and a large increase in WFH. After an increase in WFH, most classes are more prone to take up another activity-travel pattern. In both cases, most classes have an increased probability of transitioning towards the low mobility class, which underpins more sustainable patterns. Nonetheless, more diverse results appear for a small increase in WFH, and significant transitions towards other car profiles appear. Analysing the impact of a small increase on class sizes confirms this. Overall the car class sizes remain relatively high after a small increase in WFH. Thus, an increase by 1-3 days working from home may not lead to more sustainable activity-travel patterns in terms of trip rates per purpose and mode. After a small increase in WFH, the share of car users with many other trips is even the highest in 2021, Figure 2.

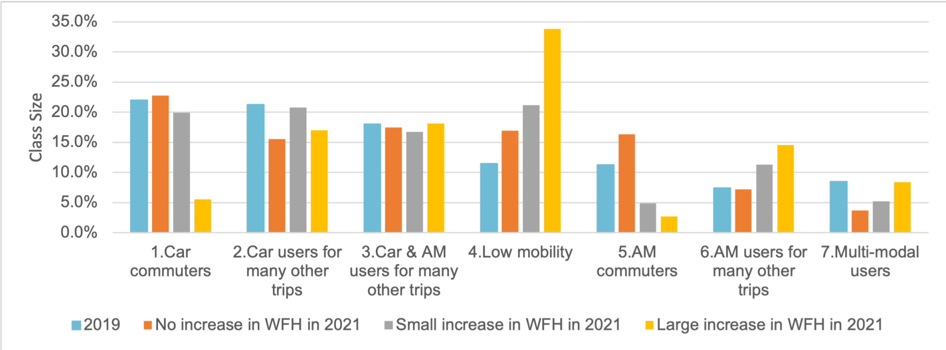

Figure 2: Shares of activity-travel patterns after (no) increase in WFH for 2019-2021

It may be expected that once people start decreasing their working from home days to only 1-3 days per week, car profiles may exceed the pre-COVID-19 shares. Large increases in WFH point more strongly towards substitution in both commute trips and non-commute trips. Nonetheless, the results show that transitions depend on initial class membership. Two classes in the 2019-2021 model appear to behave differently than other classes. The third class, active mode and car users for many other trips and the sixth class, active mode users for many other trips, are less drawn to transition towards a low mobility class. Thus, certain groups in the population seem to have a higher trip demand that also remains when increasing WFH.

The results for a decrease in WFH are not significant. Thus, no hard conclusions are drawn. Nonetheless, based on the sample in the second model, people do not shift back to their old activity-travel patterns after a decrease in WFH as much as they change to different patterns after an increase in WFH. Additionally, an increase in WFH leads to significant effects, while a decrease to non-significant effects on transitions in activity-travel patterns. This may point towards asymmetry or hysteresis of a change in WFH on activity-travel patterns. Hysteresis would mean that the effect of an increase in WFH on activity-travel behaviour is not fully reversed if WFH decreases again. Causes for this lasting behavioural adaptation may be the creation of new habits, routines and daily schedules or task sharing with other household members while WFH. Nonetheless, further research is needed to confirm or deny this assumption, given the sample limitations of the second model. For the time being, these findings do not exclude the existence of structural changes in working and travel behaviour.

The results of this research lead to theoretically novel findings. The application of LTA, a longitudinal clustering method, sheds light on complex transition behaviour in the population during- and post-COVID-19 measures. The results show that activity-travel patterns before a change in WFH and the level of an increase in WFH matter for the impact of WFH on transitions. Depending on the initial class membership, differences in transitions emerged. To a certain extent, all effects of WFH on travel, substitution, complementarity, modification, and neutrality exist in the population, but these depend on initial class membership. Thereby, this research uncovers up-to-date undiscussed heterogeneities in adapted travel behaviour which appear when increasing the extent of WFH. The further use of clustering methods to study the relation between WFH and travel behaviour and accounting for past activity-travel patterns or travel behaviour is recommended.

For policy-makers, the results imply that a small increase in WFH, less than at least three days per week, does not necessarily lead to improvements in sustainability and accessibility. Based on the results of this study, a large increase in WFH leads to more sustainable activity-travel patterns. Many people adopt a low mobility pattern after a large increase in WFH, which improves accessibility. However, from a societal perspective, low mobility behaviour raises physical health concerns. While a small increase in WFH also leads to rises in shares for more sustainable patterns, car patterns remain high as well, especially for car users with many other trips. Thus, in case of only small increases in WFH, the net effects on sustainability may go towards zero as some people decrease travel, but others increase travel. Nevertheless, it needs to be kept in mind that this study only analysed trip rates per purpose and mode, a small increase in WFH may still lead to a peak-travel reduction, which benefits accessibility. Further analyses should investigate peak-travel to conclude on the accessibility benefits of small increases in WFH. At the same time, governments and employers should take measures to counter-act low mobility associated with WFH.

Generally, the analysis of transitions shows that people are less inert to keep their activity-travel patterns when an increase in WFH appears. Thus, an increase in WFH presents a window of opportunity for travel behaviour change. Hence, policy-makers may use moments of increased WFH to stimulate additional changes in travel behaviour, such as modal shifts towards sustainable modes, since people are receptive to change in these moments.

Contents

Abbreviations

Abbreviation	
AM	Active mode
BIC	Bayesian Information Criterion
BVR	Bivariate Residuals
COVID-19	Coronavirus Disease 2019
CBS	Centraal Bureau voor de Statistiek
EU	European Union
KiM	Kennisinstituut voor Mobiliteitsbeleid
LCA	Latent class analysis
LTA	Latent transition analysis
MPN	Dutch Mobility Panel
PKT	Person kilometers of travel
PT	Public transport
SCMN	Substitution, complementarity, modification, neutrality
SEM	Structural equation modelling
SQ	Sub-question
TTB	Travel time budgets
VMT	Vehicle miles travelled
WFH	Working from home

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1 Introduction

This chapter explains the background information for the studied problem, the problem definition in relation to the policy relevance, the scientific relevance and the knowledge gaps. A series of research questions are presented to guide the research to approach the identified objectives.

1.1. Background

In December 2019, the coronavirus disease 2019 (COVID-19) outbreak was reported from Wuhan, China (WHO, n.d.). In early 2020, the coronavirus spread to many countries worldwide. The COVID-19 virus was marked by fast-transmission rates and considerable mortality rates. Governments reacted with measures such as strict travel restrictions and the recommendation or obligation to work from home (WFH) to reduce the spreading of the virus (Kramer & Kramer, 2020). According to an international survey in European and North American countries, about 45 % of the people worked from home in the early days of the pandemic (Coroiu et al., 2020).

During COVID-19, extreme reductions in transport demand occurred, which led to decreases in time losses, emissions and energy consumption and by this favoured the accessibility and sustainability of mobility system (Du et al., 2021). Accessibility was favoured as less congestion and crowding occurred on the roads and in public transport (PT) (Hamersma et al., 2021). Sustainability benefits came from overall reduced mobility during COVID-19 and notably less peak travel, leading to less congestion and fewer emissions.

1.2. Problem definition and policy relevance

To reach sustainability goals of the mobility system while remaining accessible, the Netherlands needs to make changes to its mobility system to provide a system that allows citizens to travel quickly, comfortably and safely (Rijkswaterstaat, n.d.). Besides changes in the mobility system, certain policy levers exist to further manage the change towards sustainability and particularly accessibility by optimizing the use of the current infrastructure. During the pandemic, the large-scale WFH *'experiment'* showed that WFH may be a viable policy lever to increase sustainability and accessibility of the mobility system (Beck et al., 2020).

The recommendation or obligation to WFH was, besides crowd-avoidance measures, travel restrictions and closed educational establishments one of the critical factors leading to lower mobility and congestion in the Netherlands (Hamersma et al., 2021). About half of the Dutch working population exchanged their workplace for the home office due to the pandemic, many did so full-time (Hamersma et al., 2020). Research around the world showed that the experience with WFH was relatively positive, and a substantial share of Dutch workers wish to continue to work from home for 1-3 days per week post-pandemic (Corona Datenplattform, 2021; Hamersma et al., 2021). On March 23rd 2022, the Dutch government lifted the final COVID-19 restrictions, including the advice to work from home (Government of the Netherlands, 2022). For the time being, this marked the end of governmental COVID-19-related WFH policies in the Netherlands.

Nonetheless, against the background of possible accessibility and sustainability benefits, the Dutch Ministry of Infrastructure and Water Management (IenW) wants to stimulate WFH post-measures (Hamersma et al., 2021). WFH can enhance the accessibility of the mobility system thanks to reduced commute trips during peak hours. Thereby, WFH can reduce crowding and congestion during rush hours (Hamersma et al., 2021). In this context, it is fundamental to understand developments in WFH and eventual structural changes therein and the impact of WFH on travel patterns (Hamersma et al., 2021).

However, to critically assess the benefits of stimulating WFH, the effects of WFH on all forms of travel must be known. Existing research underpins that WFH and travel behaviour are in an inherently complex relationship (Andreev et al., 2010; Mokhtarian, 1991b). While reductions in commute trips can bring attractive mobility benefits, a structural increase in WFH can have consequences beyond commute travel. Forecasts expect that a decrease in commute travel can lead to complementary travel for non-work purposes, which emphasizes the importance of studying all forms of personal mobility instead of purely focusing on commute travel to assess the transport benefits of WFH (Hamersma et al., 2021; Buitelaar et al., 2021).

Besides concerns about complementarity in non-work trips, changes in travel modes are increasingly detected as a COVID-19 consequence. Notably, car shares remained high or increased, while public transport (PT) shares dropped drastically and active modes (AM) gained in popularity (De Haas et al., 2020; Currie et al., 2021). The exogenous shock caused by COVID-19 can be a window of opportunity to alter habitual work and travel behaviour (Ton et al., 2022). Although a decrease in car commutes due to increased WFH would benefit the environment, liveability and accessibility (Hamer et al., 1991), significant adoptions of WFH were seen for PT commuters (Hamersma et al., 2020). Thus, the potential of realising sustainability benefits decreases (Ton et al., 2022). This further underpins the complexities of stimulating WFH. Eventually changing habits and travel behaviour can substantially impact the operations and planning of public transport systems. Hence, it is crucial to improve the understanding of the overall effects of WFH, including related changes in mode use. Research shows that people who work from home spend less time on PT (Ozbilen et al., 2021). It needs to be revealed how travel patterns evolve after adopting WFH. Developments in activity-travel patterns should be studied from a pre-COVID-19, COVID-19 with measures to a short-term post-measures perspective to study evolving behaviour. It is crucial to analyse change over time and detect trends in subgroups to understand possibly structural effects on the mobility system.

Given the above, it is not known whether WFH indeed leads to sustainability and accessibility benefits when accounting for total personal daily travel. How developments in WFH extents impact activity-travel patterns in the population must be studied. People have heterogeneous lifestyles and are likely to adapt their activity-travel patterns differently regarding trip rates and modes when adopting WFH. Uncovering the nature of changes in travel behaviour after a change in WFH allows policy-makers to understand and assess the consequences of stimulating WFH and whether changes lead towards more or less sustainable mobility profiles and to what extent.

1.3. Scientific relevance and knowledge gaps

Although the stimulation of WFH may be a policy lever to increase the accessibility of the mobility system due to reduced commute trips, the full effect of WFH on overall personal mobility is not known.

The relationship between WFH and travel has been studied for decades. Still, diverse results exist in literature. Some studies point towards substitution of commute and non-work travel while others underpin complementary effects of WFH (Andreev et al., 2010; Elldér, 2020). Recent studies deploying representative datasets mostly point towards complementarity of WFH and travel, thus, more travel by people who work from home (Budnitz et al., 2020). Most recent studies deploying representative national data do not use longitudinal data to study changes in travel related to WFH. Thus, these existing studies compare travel behaviour of people who work from home to the one of people who do not. Thus, revealed differences may also stem from unobserved heterogeneity between people who work from home and those who do not, and not from WFH per se (Caldarola & Sorrell, 2022; Mouratidis et al., 2021). Earlier research, which studied travel behaviour change after adopting WFH, reported substitution effects of WFH, pointing towards a reduction in travel for commutes and non-work travel (Mokhtarian, 1991b; Hamer et al., 1991). However, these early studies were limited to demonstration projects and small sample sizes (Mokhtarian et al., 1995). Beyond that, ICT has developed enormously in the meanwhile. Elldér (2020) pronounce a need for more longitudinal studies to analyse potential rebound effects of WFH, such as consequences for non-work travel in more detail. Thus, recent insights on intra-personal changes in travel behaviour after the adoption or an increase in WFH present a first knowledge gap. COVID-19 can be considered a *'natural experiment'* during which many workers adopted WFH. This provides the unprecedented opportunity to study the effects of adopting WFH on travel patterns outside demonstration projects, using large-scale national data. This context allows conducting a before-after study.

Next, existing WFH and travel literature mostly studied the effect of WFH on single modes (Elldér, 2020; Lachapelle et al., 2018; Ozbilen et al., 2021) or on single activities (Budnitz et al., 2020; He & Hu, 2015; Zhu, 2012). To date, no study attempted to reveal an effect of WFH on multiple forms of travel and, by this, on comprehensive travel or activity patterns. Beyond this, no study simultaneously considered modes and travel activities, while a relation between both can be synthesized. For instance, Elldér (2020) found that full-day WFH is related to more active travel, which naturally presents travel for non-work purposes. Accounting for overall personal activity-travel patterns allows clustering people based on simultaneous travel by mode for different activities. Such a definition of patterns allows studying the effect of WFH on multiple modes and activities simultaneously.

Furthermore, prior to the pandemic, WFH was a choice related to self-selection. During COVID-19, a majority of employees were forced to adopt WFH. This fundamental difference makes it likely that effects on travel may differ from past studies. Virtually no published literature attempted to investigate the effect of WFH on all forms or personal travel during a pandemic using longitudinal data. Existing attempts in the COVID-19 context used retrospective data and did not consider all forms of travel (Campisi et al., 2022; Riggs, 2020).

Thus, this study contributes to general WFH and travel literature and COVID-19 travel behaviour change literature by studying switches in activity-travel patterns after adopting WFH. First, it adds to the scarce body of longitudinal studies investigating the effects of WFH on activity-travel by deploying national representative datasets. Second, it is the first research to study the effect of WFH on comprehensive activity-travel patterns. Third, intra-personal changes in activity-travel patterns after a change in WFH have not been studied in the COVID-19 context. However, these may bring important insights into potential persisting structural changes. Against this background, disaggregate individual-level data analyses can show a clearer picture of trends in sub-groups of the population. Such analyses allow understanding the nature of the behavioural change, which remains hidden in aggregate analyses.

1.4. Research objective

Integrating the identified knowledge gaps, this work investigates the influence of changes in WFH on adopted activity-travel patterns to gain a comprehensive picture of adaptations in the population in the COVID-19 context.

Next to earlier COVID-19 data, which investigates the adoption of WFH, analysis of May 2022 data in the Netherlands allows giving first indications about changes in WFH and travel behaviour post-pandemic. Hence, this research also identifies whether WFH expectations hold in the transition phase of lifting measures and related consequences. This increases the knowledge on the adoption of WFH and related impacts on activity-travel patterns. Thus, the findings deliver input for policy-makers to understand and assess the consequences of stimulating WFH post-pandemic. Beyond this, the findings also serve as an input for policies that alter behaviour related to WFH, commuting and overall personal mobility. Insights also allow public transport operators and authorities to estimate future effects and adjust their planning accordingly.

1.5. Research questions and approach

In line with the objective of this study, the main research question is as follows:

How did changes in WFH influence activity-travel patterns during the pandemic in the Netherlands?

As this research aims to test the effect of a change in WFH on activity-travel behaviour, a quantitative approach is chosen. Large, longitudinal datasets are required for the study purpose. For this research, longitudinal panel data from the Dutch Mobility Panel (MPN), collected by the Netherlands Institute for Transport Policy Analysis (KiM), is deployed. Generally, about 2000 Dutch households form the MPN. During the pandemic, the KiM conducted special COVID-19 measurements in addition to the yearly measurement in September-November. By this, data at different time points in the pandemic is available. The MPN includes amongst others WFH and travel diary data. The data is described in detail in Chapter 3.

Four sub-questions (SQs) guide the research to answer the main research question (RQ).

1) What are the conceptual relations between WFH and activity-travel patterns during the pandemic?
Travel patterns observed when working from home in the past fifteen years are not a good indicator for the future due to remarkable changes in WFH levels during COVID-19 (Caldarola & Sorrell, 2022). The exogenous shock caused by COVID-19 led to drastic changes in working and travel patterns. Thus, a theoretically and contextually grounded conceptual model is needed to guide the research. First, international scientific literature on COVID-19 travel behaviour change is reviewed to understand pandemic-related changes in travel behaviour. Second, the Dutch WFH situation is analysed to understand the national context. Such information is drawn from reports issued by Dutch knowledge institutes. Third, international scientific literature on the interaction of WFH and travel is analysed to identify theoretical and empirical relationships. The same literature gives essential insights on variables that should be controlled for when assessing changes in activity-travel patterns related to WFH. Together these insights lead to the formulation of a conceptual model to guide the subsequent phases of this research.

2) What changes in the extent of WFH emerged during the pandemic?
Recent studies investigating the effect of WFH on travel are mostly cross-sectional and compare the travel behaviour of people who work from home to travel of those who do not. In contrast, this study makes use of longitudinal panel data to study intra-personal change after a change in WFH. To study the impact of a change in WFH, a diversity of WFH intensities is desirable. Synthesising policy relevance, theoretical and empirical insights (identified in SQ 1), and descriptive analyses of the MPN data, increases and decreases in WFH are studied. The results of this SQ are used to operationalise a change in WFH variable for the subsequent research steps.

3) What activity-travel patterns did workers adopt in the Netherlands throughout the pandemic?
Existing WFH and travel studies did not consider multiple modes and trip purposes simultaneously to study the effect of WFH on travel. This research considers both at the same time to present a holistic picture of personal daily mobility in the Dutch working population. Against this background a clustering method is chosen as it allows studying multiple variable levels simultaneously. Next, activity-travel patterns are not known beforehand as they result from individual behaviour and by this emerge from the data. Hence, a Latent Class Analysis (LCA) is conducted as the optimal number of classes does not need to be known upfront. Besides this, the LCA is a natural choice considering the subsequent analysis.

4) Which changes in WFH influence transitions in activity-travel patterns over the pandemic?
After identifying change in WFH variables and activity-travel patterns, the relationship between changes

in WFH and transitions in identified activity-travel patterns is analysed and assessed. For this purpose, a longitudinal extension of the LCA, Latent Transition Analysis (LTA), is applied. This quantitative analysis is chosen as it is the only approach to account for dynamic travel behaviour over time. By letting changes in WFH interact with transitions, effects of changes in WFH on activity-travel patterns can be studied.

Chapter 3 describes the LCA, the LTA and the data including advantages and limitations in depth.

1.6. Scope

The following scoping decisions delineate the research. Nonetheless, the literature analyses to answer the first sub-question further refine the scoping.

- This thesis focuses on analysing personal daily mobility instead of household travel. Although general WFH and travel studies emphasise including household travel behaviour, this is not done as the special COVID-19 measurements of the MPN are at a personal level (de Abreu e Silva & Melo, 2018).
- This study focuses on daily personal travel behaviour and, thus, excludes holiday and occupational travel.
- The study solely focuses on home-based telework referred to as WFH. Distance education is out of scope, as expected changes for WFH are higher (Hamersma et al., 2021). Additionally, data availability for WFH is higher than for distance education in the MPN.
- Other than travel-related effects of WFH, such as well-being, stress, workplace and residential choices go beyond the scope of this thesis.
- Peak hour travel is also out of scope for this thesis.

1.7. CoSEM relevance

Stimulating WFH for transport reasons presents an intervention into a complex socio-technical system. It is critical to set correct system boundaries to study the effect of this policy intervention. WFH has effects that go beyond commute travel and the work-life. For instance, if only commute travel is analysed WFH may appear beneficial for accessibility reasons. However, if the system boundaries are enlarged to other non-work travel, the benefits of WFH are not straightforward anymore, as existing literature shows. The mathematical models used in this research are technical tools that assist policymakers in assessing the consequences of WFH as a policy-lever. Furthermore, the results are relevant for a variety of parties: governments, public transport companies and employers. This underpins the interconnectedness of the system and the public and private values that are at play, which is typical for a CoSEM thesis. The social context and temporal setting given the pandemic, is one of the drivers of this research. Thus, also the results need to be evaluated with great care and in regular intervals to assess whether an actual structural effect persists and how the WFH and travel dynamics develop. Given these complexities, the topic at hand presents an example of a CoSEM thesis.

1.8. Thesis outline

This thesis is divided into six chapters. Chapter 2 presents background information on COVID-19 travel behaviour change, WFH in general, WFH during COVID-19 in the Netherlands and the relation of WFH and travel. This chapter concludes with synthesising the gained insights into a conceptual model to guide the research. Chapter 3 describes the chosen methods, the data sources and preparation and the sample descriptives. Chapter 4 discusses the model operationalisation and by this the selection of a change in WFH variable. Chapter 5, identifies the existing activity-travel patterns for workers in the Netherlands by conducting a Latent Class Analysis. Next, Chapter 6 presents the dynamic part of the analysis. In this chapter, the effect of a change in WFH on transitions between activity-travel patterns is studied. Chapter 7 answers the SQs and main RQ, discusses and evaluates the findings of the previous chapters, formulates policy implications and lastly, opens the frame for possible future work.

2
Literature review and conceptualisation

This chapter positions the research in existing literature defines important concepts and clarifies the research contribution and scope. To do so, this chapter is organised into four sections:

1. Section 2.1 presents insights from (international) scientific literature on COVID-19 travel behaviour change.
2. Section 2.2 introduces general notions of WFH and elaborates on the Dutch WFH context, pre-, during- and post-pandemic.
3. Section 2.3 reviews general scientific WFH and travel literature. Here definitions and theories are explained, conceptual relations are discussed, and existing empirical studies are reviewed.
4. Section 2.4 synthesises the insights from the previous sections into a conceptual model, which provides the frame of this research. This section answers the first sub-question:
   What are the conceptual relations between WFH and activity-travel patterns during COVID-19?

2.1. COVID-19 travel behaviour change

Research results indicate that the pandemic could permanently change how people work and travel (Beck & Hensher, 2021). Travel behaviour changes during COVID-19 can be drawn back to the fear of infections and policies by governments to stop the spreading of the virus. Some of these policies were, for instance: closed destinations or visitor limitations, curfews, but also the recommendation or obligation to WFH and recommendations to avoid public transport to avoid crowding. The latter two are interlinked.

The review results below are not meant to present an extensive overview of all travel-related changes during COVID-19, but solely present main trends in activity participation, trip rates and modes. These insights are important to contextually ground the conceptual model and expectations of this research in the COVID-19 context. The following two topics are discussed:

1. **Out-of-home activity participation during COVID-19**
2. **Travel by mode**

2.1.1. Out-of-home activity participation

Research shows that during the pandemic the out-of-home activity participation was severely influenced, which impacted personal daily activity-travel behaviour.

Major changes from business meetings and long-distance commutes to WFH and from instore-shopping to online shopping arose in the pandemic (Shamshiripour et al., 2020). Thus, certain out-of-home activities got transferred to the home environment. Although people can engage in non-mandatory activities at home, individuals still have the need and desire to take non-mandatory trips (Loa et al., 2021).

Against this background, De Haas et al. (2020) indicate that the shares of shopping and walking or touring show a substantial rise at the time of their survey in March 2020. The rise in walking and touring is linked to the rise in roundtrips, trips with identical origins and destinations. They add that the most important reason for such a trip was cycling or walking tours in early 2020 (De Haas et al., 2020). According to De Vos (2020), such recreational activities can be essential to weaken some of the negative influences of reduced physical activity and isolation.

Bohman et al. (2021) analysed changes in trip frequency for different mandatory and non-mandatory activities via qualitative content analysis. They found that new activities were mostly outdoor activities. By this, they show similar results as De Haas et al. (2020). Similarly, Astell-Burt and Feng (2021) found that WFH was linked to more extended and more regular visits to outdoor spaces, also underpinning non-mandatory activities. Bohman et al. (2021) explain that long-term changes in WFH may lead to a reduced number of trips. However, the previous statement about increased activities can also hint towards increased other non-mandatory trips, complementary trips, which are prominently discussed in general WFH and travel literature.

Generally, Beck et al. (2020) found that travel activity started to return when the measures started easing, especially for shopping, recreational or social purposes. Similarly, De Haas et al. (2020) found that the vast majority of people who reduced their activities at the beginning of COVID-19 do not expect to keep reduced outdoor activity levels after the pandemic. Hence, the demand for non-mandatory travel activities likely bounces back post-pandemic.

2.1.2. Travel by mode

Another notable change is that COVID-19 not only favoured a shift in out-of-home activities but also in modal preferences. Research found an increase in shares for active modes (AM) (e.g. walking and cycling) (Zhang, 2021). This may have consequences for the future. For instance, about 20 % of a Dutch representative sample expect to walk and cycle more (De Haas et al., 2020). Thus, even-though overall mobility decreased, the modal share of active modes seems to have been close to pre-COVID levels and, in some cases, even exceeded these (Loa et al., 2021; De Haas et al., 2020).

At the same time public transport (PT) ridership levels drastically fell (Zhang, 2021; De Haas et al., 2020). In this context, De Haas et al. (2020) showed that it is important to investigate which people are more prone to work from home and how they commuted pre-pandemic. They found that people commuting by public transport were likelier to spend more hours WFH in March 2020. Thus, the recommendation to avoid PT is closely related to WFH during the first COVID wave. Public transport use is a continuously discussed concern in relation to the pandemic, given the fear that people will permanently switch from PT to less sustainable individual modes such as the car.

Next to the increase in active modes and decreases in PT, Bohman et al. (2021) and Currie et al. (2021) find modal shifts towards higher car use in Sweden and in Australia. In the Netherlands, the relative importance of car trip shares only slightly changed (De Haas et al., 2020). However, considering the extreme decrease in PT trip shares, the minimal changes in car trip shares do not point towards more sustainable behaviour.

The just mentioned shifts can partly be explained by the promotion of cycling and walking by some governments to remain active, the advice to use individual transport, the recommendation to avoid public transport (PT) (Bohman et al., 2021) and the recommendation or obligation to WFH which led to a decrease in commute travel. Decreases in commute travel are in direct relation with mode use. For instance, PT is frequently used by commuters (De Haas et al., 2020). Related to this, De Haas and Faber (2022) showed that people's attitudes towards modes drastically changed in the pandemic. Thus, policy-makers must observe the developments concerning individual travel modes and the reduced preference for PT due to the pandemic (De Haas et al., 2020).

2.2. Working from home

2.2.1. Historical backdrop

Although the term WFH gained popularity in the COVID-19 context, transport researchers have been studying WFH, or related concepts such as telework or telecommuting at least since Nilles (1976) proposed telecommuting as a strategy to reduce traffic congestion, pollution and face the scarcity of resources. Businesses started considering WFH during the oil embargo in the seventies, hoping to be more resistant to fuel scarcity (He & Hu, 2015). The underlying thought was that telework may decrease travel demand and help to solve congestion problems (Ozbilen et al., 2021). These thoughts regained relevance in COVID-19, as many improvements in terms of sustainability and accessibility could be seen. However, as shown in the subsequent sections, actual reductions in travel have low evidence. Still, WFH can lead to substitution, complementarity, neutrality or modification (mode use, peak travel etc.) of travel behaviour at an individual level.

The interest in WFH started growing along with the progress in ICT solutions. Home-based telework, as known today, arose in the 1990s given fast ICT breakthroughs, such as the availability of affordable and capable computers, the Internet, reliable and inexpensive broadband (Harpaz, 2002). At this time, research issues were centred around workforce topics such as employer motivation and satisfaction, technology-related topics investigating the role of ICT and organizational subjects about the adoption of WFH and mediating factors and environmental issues (Siha & Monroe, 2006). Since the beginning of the 1990s, environmental topics related to WFH have gained increased interest and even more so in the 21st century. Environmental issues are split into impacts of the technology on the one hand and transportation aspects on the other hand (Siha & Monroe, 2006). This thesis is concerned with the latter, more precisely as introduced in Chapter 1, with activity-travel patterns and modes use.

The following sub-section elaborates on the definition of WFH versus telework and telecommute to shed light on subtle differences.

2.2.2. Definition of working from home

Working from home became a prominent term in the COVID-19 context. Still, in general research this concept is referred to as teleworking, telecommuting, virtual office, remote work or home-office (Andreev et al., 2010; Laumer & Maier, 2021; Mokhtarian, 1991b; Sullivan, 2003). Transport research mostly uses telecommuting or teleworking, often used interchangeably with WFH (Mokhtarian, 2021). Still, some types of WFH, such as home-based businesses or working overtime in the evening or weekends, are not commonly defined as teleworking or telecommuting by transport researchers as these WFH types do not substitute otherwise occurring commute trips (Mokhtarian, 1991a). Even between teleworking and telecommuting, subtle differences exist. While telecommuting replaces commute trips, this is not necessarily the case for telework (Mokhtarian, 1991a). Nonetheless, research often uses both terms interchangeably.

In general research, no agreed-on definition of telework or telecommute exists (Sullivan, 2003). Transport research commonly accepts the definition by Mokhtarian et al. (2005) for telecommuting. They define telecommuters as "*salaried employees of an organization [that] replace or modify the commute by working at home or a location closer to home than the regular workplace, generally using ICT […]*" (Mokhtarian et al. 2005, p. 427). In their literature review, they indicate telework intensity levels ranging from once per week to once per month. Thus, working from home is often used as an umbrella term within this field with multiple intensity levels (Mokhtarian, 2021). As a result, differences in definitions of WFH or telework variables are important while investigating related research (Mokhtarian, 2021). These definitions mostly relate to the following dimensions (Sullivan, 2003):

- ICT use
- Proportion of decentralised work time (informal overtime, occasional, full-day, part-day, multiple days per week, per month etc.)
- Contractual agreement of workers (employed vs self-employed/ home-based business workers)
- Work Location (fixed workplace vs home, other remote places than home)

Understanding and acknowledging the difference between distinct types of WFH categories is essential when analysing the association with travel as effects can differ significantly. The review in Section 2.3.3 shows that the effects on travel of full-day WFH differ significantly from part-day WFH (Elldér, 2020). For instance, a person working from home full day does not have any work-related trips on that day. However, somebody who works from home partial-day or does overtime has the same amount of work-related trips as somebody who works full-time from the workplace.

Nonetheless, in practice, clear distinctions in different WFH types may be difficult depending on the datasets or existing travel surveys. Against this background, Sullivan (2003) argues that project-specific definitions of WFH by different studies are practical and inevitable. Distinctions between types of telework and homeworking have gotten much focus in the debate about a suitable definition for teleworking. Literature argues that the crucial difference between a teleworker and a homeworker is the use of ICT. However, this may lead to an arbitrary distinction between homeworkers and teleworkers. Although people who work from home without using ICT may be a minority, this does not necessarily mean that they should be excluded from all studies that try to shed light on the concept and consequences of working at home. Finally, the sample (telework and/or homeworkers) used to study working from home phenomena highly depends on the research purpose (Sullivan, 2003).
Considering the travel pattern focus of this thesis and the WFH context of the COVID-19 pandemic, this research focuses location-wise solely on home-based teleworking/telecommuting, referred to from now on as WFH.

2.2.3. WFH effect and adoption

Effects of WFH
Several studies found that WFH can positively influence productivity, amongst others, given the absent commute (Kazekami, 2020). Next, WFH can enhance perceived work-life balance and autonomy, and it may promote job satisfaction (Gajendran & Harrison, 2007). These benefits aside, WFH still comes with a serious risk of professional isolation, which in turn can negatively impact the delivered performance (Golden et al., 2008). However, these effects are not part of the scope of this thesis.

A substantial body of literature discusses travel behaviour related to WFH, as people working from home reduce or eliminate the travel to the regular workplace (Mouratidis et al., 2021). Still, as already hinted at in the previous section this relation is also not straightforward in general WFH and travel literature and likely even less during COVID-19.

Considering the above, differences between people adopting WFH pre-COVID and during/post-COVID-19 may exist. Thus, differences in WFH impacts on travel behaviour in pre- and post-COVID-19 may also exist. Most notably, a conceptual difference exists in who adopted WFH. Pre-COVID-19 people mostly self-selected themselves to adopt WFH. Thus, they worked from home by choice and may have done so to move to a different area or similar. Given the external change triggered by the pandemic, many people were forced to adopt WFH. This may be similar to the impact of a disruption or major event on travel behaviour.

Adoption of WFH
Generally, pre-COVID, the adoption of WFH depended on the job type, the type of working arrangements and culture, and it was connected to specific personal characteristics such as education level, income and age (de Graaff & Rietveld, 2007). Next to this, the adoption also rested on managers' control and trust, individual work-life balance considerations and household dynamics (Vilhelmson & Thulin, 2016).

COVID-19 accelerated the adoption of WFH for several sectors (Mouratidis et al., 2021). The KiM reviewed and analysed explanatory factors for adopting WFH pre-and during-COVID-19 for the Netherlands (Hamersma et al., 2020). Table 2.1 summarises explanatory factors for the adoption of WFH pre- and during-COVID-19.

Pre-COVID-19 just as during COVID-19, the extent of WFH differs enormously between **sectors, functions and occupation types**. The KiM found that employees from the automation and ICT sector work from home more often, while employees from the industry and production sectors do so least often. Office workers worked from home slightly more often before corona than the 'average' worker. In addition, at the start of the crisis (March/April 2020), workers in education also reported that they worked from home more often than workers in the industry and production sector (Hamersma et al., 2020).

Generally, the highly educated and elderly (55 years and older) are more likely to work from home. Statistical analyses on the MPN data from autumn 2019 showed that **educational level and age** significantly influenced the extent of WFH before the pandemic. Relatively young employees (up to 35 years) work from home significantly less often than employees aged 35-55 years, who in turn work from home less often than older employees (55 years and older) (Hamersma et al., 2020). Next, (pre-corona) results show that highly educated people work from home more often than less educated people (Hamersma et al., 2020).

While the previous paragraphs discuss the meditating factors for the general adoption of WFH, the COVID-19 period is marked by changes in WFH and also there facilitating factors are emphasized.

Table 2.1: Explanatory factors for the adoption of WFH pre- and during-COVID-19, based on Hamersma et al. (2020)

Explanatory Factors	Pre-COVID-19	During COVID-19	Relation with WFH
Sectors	•	•	-Employees from the automation and ICT sector more likely to WFH -Employees in the industry and production sector least likely -At the start of COVID workers in education worked from home more than people in the industry and production sector
Occupation Type	•	•	-ICT employees and managers highest possibilities for WFH -Service professions and employees in transport and logistics have the fewest opportunities to WFH
Age	•	•	-Young employees (up to 35 years) work from home less often than employees aged 35-55 years -Employees aged 35-55 years work from home less often than older employees (55 years and older)
Education	•	•	Highly educated people work from home more often than less educated people
Gender	-	•	Women were more likely to work from home than men during the corona crisis
Income	-	-	Differences between higher and lower incomes do not remain significant after correction for other background factors
Job suitability	-	•	Increases in WFH were stronger for workers who judged their job suitable for WFH
PT use pre COVID	-	•	Pre-COVID PT commuters are more likely to work from home than car commuters

The KiM analysed explanatory factors for an increase in WFH in April 2020 vs pre-COVID 2019. They found that the increase in WFH during the pandemic was stronger among highly-educated people, workers who consider their job suitable for WFH and public transport commuters (Hamersma et al., 2020). People who commuted to work by public transport are more likely to work from home than car commuters. Next, the KiM found that the difference between higher and lower incomes does not remain significant on the basis of the MPN analysis after correction for other background factors. Another Dutch study, which did not adjust for other factors, found that the increase in WFH at the beginning of the pandemic was greater among high-income workers than among low-income workers (Von Gaudecker et al., 2020). Next, analyses of factors influencing the extent of WFH during the pandemic found that gender is a significant factor. Women were more likely to work from home than men during the corona crisis.[1]

Based on MPN data, the KiM finds that younger employees [2] and employees in the educational sector returned to working at the workplace at the beginning of July compared to the start of the pandemic. People who find their work suitable for WFH are relatively more likely to continue working from home than people who do not find their job suitable for it (Hamersma et al., 2020).

[1] Based on the MPN corona measurement data from July 2020. The difference between men and women is not significant based on the data at the start of the crisis (end of March/beginning of April).

[2] Younger employees means here up to the age of 35.

In summary, the level of education, pre-COVID commute mode, job suitability, gender and age are important factors considering the change in the WFH extent during COVID-19.

2.2.4. WFH in the Netherlands: pre-, during- and post-COVID-19

A national analysis is essential as WFH measures during COVID-19 and the (pre-COVID-19) extent of WFH differ per country.

Hamersma et al. (2020) analysed Dutch representative studies and provided information on the extent of WFH pre-, during-COVID-19 and post-COVID-19 expectations. These insights are summarised in Table 2.2 and discussed below.

Table 2.2: WFH pre-, during-, post-COVID-19 in the Netherlands, based on Hamersma et al. (2020) and De Haas et al. (2021)

	WFH (occasionally)	**WFH (almost) full-time [1]**	**Share of WFH people doing so full-time**	
Pre covid	29-39% of workers[2]	6% of workers	15% of workers WFH	
During Covid				
March-April 2020	45-56% of workers	39% of workers	70% of workers WFH	
May-July 2020	slight decrease	decrease	about 35 % of workers WFH	
September -October 2020	slight decrease	decrease	-	
Post Covid Expectations[3]	**Share of people expecting to WFH more**	**Share of people expecting to WFH more in the coming months**	**Share of people expecting to WFH more in the long term**	**Share of people expecting to continue WFH full-time**
March-April 2020	40-60%	-	-	-
May-July 2020	Increase	62%	45%	10%
September -October 2020	Increase	-	47%	-

[1] Full-time refers to 3/4 of the working hours spent at home
[2] Ranges indicate that the numbers are based on different Dutch representative studies reviewed by the KiM, and MPN analyses by the KiM
[3] Working from home more means compared to prior the pandemic

Based on different Dutch **pre-COVID-19** surveys, Hamersma et al. (2020) found that already before the pandemic, 1 out of 3 employees sometimes worked from home and about 6 % did so (almost) full-time. This evaluation shows to be rather consistent across multiple studies representative of the Netherlands. These WFH numbers rank the Netherlands second behind Sweden for the proportion of people who worked from home in the European Union (EU) pre-COVID-19 (Sostero et al., 2020).

According to Dutch COVID-19 studies analyzed by the KiM, a large proportion of workers complied with the government's WFH advice **during** the pandemic. As a result of the pandemic, the share of working people who worked (partly or completely) from home increased from about 1 out of 3 workers before the corona crisis to 45-56 % at the start of this crisis. Also, the proportion of employees who fully worked from home significantly increased from about 6 % before corona to about 39 % in April 2020 (Hamersma et al., 2020).

However, the share of people working from home decreased slightly between May and July 2020 and September-October 2020. Especially the share of working people who worked (practically) entirely from home decreased. This is likely due to the cabinet's relaxation of corona measures in the period from May to July 2020. At the end of March 2020, more than 70 % of workers working from home worked (almost) entirely from home; this proportion dropped to just under half in July 2020. Nonetheless, the share of people who worked from home was still considerably higher than before the pandemic. This insight is shared by almost all Dutch studies that provide information about this matter (Hamersma et al., 2020)[3].

In the debate about the impact of WFH on travel, the **future expectations** for WFH (post corona) build an essential starting point to analyse post-corona measures travel behaviour. Most studies reviewed by Hamersma et al. (2020) conclude that a significant proportion (40 to 60 %) of people who worked from home during the pandemic expect to work more from home when the pandemic ends than they

[3] The differences between studies appear to be mainly caused by different samples, definitions of working from home and the period in which the investigation took place (Hamersma et al., 2020).

did before. This share increased during the period of March-July 2020, but also in September/ October 2020 (De Haas et al., 2021). Reasons for the increase may be that workers became better and more familiar with WFH over time, but also, fewer people continued to work from home. People who no longer work from home are less likely to continue WFH after the pandemic. Also, there seems to be a difference between the short-term and long-term intentions (post-pandemic). In 2020, 62 % expected to WFH more in the coming months, while 45 % expected to work from home more in the long-term (Hamersma et al., 2020).

After reviewing multiple Dutch studies and conducting analyses on MPN data, Hamersma et al. (2020) and De Haas et al. (2021) conclude that a majority of employees expect to continue WFH for between 1 and 3 days once the pandemic ends. Thus, most people who worked from home during the pandemic would prefer alternating between WFH and the workplace. Concerning full-time working from home, no more than 10% of people who worked from home expect to continue WFM full-time after the pandemic ends. Concerning these 1-3 days, results showed that the proportion of people who expect to work from home for 1-8 hours is approximately equal to the proportion who did this before the pandemic. In particular, the number of working people who would work from home for 2-3 days would increase, based on the expectations of the respondents (De Haas et al., 2021).

Pre-COVID-19 WFH and travel studies may inform about a conceptual model to study the effect of WFH on travel patterns, but COVID-19 travel behaviour change and WFH developments need to be considered as well. Having introduced the latter, general WFH and travel literature is reviewed in the next section.

2.3. WFH and travel

The transportation perspective of WFH can be analysed from a societal, organisational or individual level (Andreev et al., 2010). This thesis focuses on the individual-level perspective.
Mokhtarian (1991b) presents several major research hypotheses concerning the relation how the adoption of WFH can affect individual travel patterns:

- *Frequency:* Mandatory (work) trips are expected to decrease while non-mandatory trips eventually increase. Reasons for the increase can be a psychological need for travel or new availability of a vehicle for other household members [4].
- *Time-of-day/week:* Trips may be scheduled for off-peak hours or on different weekdays, given the new flexibility.
- *Destination/ length:* Non-mandatory trips may be closer to the residential location than the work location.
- *Mode:* Carpools may dissolve if some start to WFH. Trips may be more localised around home, and active modes become more attractive.
- *Trip chaining:* Work trip elimination may break efficient chains, leading to more one-stop trips.
- *People making the trip:* Household-level trip division may change
- *Vehicle ownership:* **Medium-term** WFH may lead to less cars at household level
- *Residential/ work location:* **Long-term** WFH may lead to moving further away from the workplace to live in a more desirable location or accepting jobs further away given the ability to WFH. In these cases, extra distances on commute days may or may not balance out saved travel on WFH days.

Although people may save travel time by eliminating their commute, this does not necessarily mean that they reduce their total travel (Mouratidis et al., 2021). Hence, at an aggregate level, reductions may not be very high. Before COVID-19, the effect of WFH on travel was not very strong. (Andreev et al., 2010). These small or absent effects may partially be attributed to several reasons. First, low adoption of WFH pre-COVID-19 may be the cause. Second, a complex relationship between WFH and travel behaviour linked to a critical question of causality may contribute as well (Mokhtarian et al., 2004). Third, the effect of WFH on travel is not straightforward, literature proposes the substitution, complementarity, modification and neutrality (SCMN) classification (Salomon, 1986; Senbil & Kitamura,

[4] The effect of WFH on travel is frequently analysed at a household level and not solely at the personal level of the person working from home.

2003). The following section elaborates on the critical question of causality and self-selection, followed by introducing the SCMN classification.

2.3.1. Direction of causality

The brief list of research hypotheses above points towards a distinction between long and short-term effects. WFH may lead to reductions in the short-term, but in the long term, theory stipulates that people may opt for residential or work relocation (Andreev et al., 2010).

The issue of self-selection or residential location and the associated direction of causality are essential aspects when investigating the relationship between WFH and travel. Existing research stipulates, at best a bi-directional relationship between WFH and travel behaviour (Mokhtarian et al., 2004).

On the one hand, self-selection partly contributes to this bi-directional relationship. People possessing the option and choosing WFH have distinct household and personal traits than others. These traits impact travel behaviour and out-of-home activities (He & Hu, 2015). The discipline is still uncertain whether activity-travel patterns are the cause for the adoption of WFH or whether people who work from home adopt these activity-travel patterns because they work from home. For example, do individuals travel more because of the time freed up by the saved commute trips, or do they need to work from home given other requirements such as child care (Asgari & Jin, 2017).

On the other hand, complexities between WFH and commute distance also contribute to the bi-directional relationship. Studies centred around whether commuting costs such as time and distance increase the WFH adoption. Several articles find that people who work from home more often have further one-way commutes (de Vos et al., 2018; Zhu & Mason, 2014; Zhu, 2012). Next, Ory and Mokhtarian (2006) found that people who work from home moved closer to their workplace, whereas commuters who moved away from their workplace started working from home after the relocation. Risk of bias exists if models do not control for an endogenous relationship between workplace and residential locations and WFH frequencies (Caldarola & Sorrell, 2022). This discussion in WFH and travel literature has analogies to the discussion on residential self-selection (Ewing & Cervero, 2010). So, causality may at best act in both directions, Figure 2.1.

Thus, self-selection and location choices make it impossible to study unbiased effects of WFH on travel behaviour without accounting for an endogenous character of WFH. If this issue is ignored, the impact of WFH on travel may be interlinked with other household and personal characteristics. Thus, the effect of WFH on travel may be biased (He & Hu, 2015).

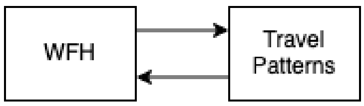


Figure 2.1: Bi-directional relation between WFH and travel patterns

In the short-term COVID-19 context, self-selection and relocation issues may be less relevant. People did not self-select into working from home, they were forced to work from home or suddenly able to do so due to national policies. WFH may have different effects for this new cohort of WFH people compared to pre-COVID-19 findings. Thus, the relationship between WFH and travel behaviour may also differ from existing findings (Caldarola & Sorrell, 2022). Given the absence of self-selection and the fact that relocation takes time, it is valid to assume an exogenous effect of WFH on travel behaviour, at least for the short term. Nonetheless, in the post-pandemic era, issues of self-selection and relocation become important research avenues again to understand the dynamics between WFH and travel behaviour. Many people adopted working from home during the pandemic and experienced advantages and disadvantages for the first time. Research shows that a substantial share of people plans to work from home more post-pandemic, as described for the Netherlands in Section 2.2.4. Thus, when lifting the mandatory WFH policies, new self-selection to work from home occurs by a likely larger share of the population.

2.3.2. Classification of interactions between WFH and travel

The effect of WFH on activity-travel behaviour is not straightforward. The classification of interactions between ICT and travel introduced by Salomon (1986) offers an overview. Salomon (1986) introduced three interactions between ICT and travel and Senbil and Kitamura (2003) added a fourth one, namely neutrality. The four first-order interactions are substitution, complementarity, modification and neutrality (SCMN). First-order interactions explained below are at the core of this thesis. Second-and third-order interactions are beyond the actual scope. However, they are relevant to remember when reflecting on long-term effects. These second and third-order interactions are work and residential relocation, land use and possible changes in social norms (Andreev et al., 2010).

First-order interactions between ICT and personal travel include the main short-term effects that WFH activities can have on travel patterns, shown in Figure 2.2 (Andreev et al., 2010).

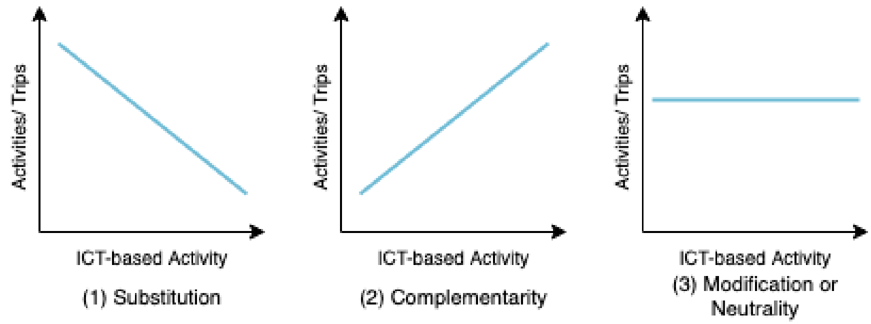


Figure 2.2: First-order interactions between ICT and personal travel, adapted from Senbil and Kitamura (2003)

Replacing the commute trip by adopting WFH leads to decreases in commuting. This effect is called substitution (S), Figure 2.2 (1), occurring when ICT leads to substitution of actual travel (Andreev et al., 2010). Nonetheless, absent commutes save travel time, which can be spent on other activities (Elldér, 2020). If this occurs, research talks about complementarity (C), Figure 2.2 (2). A complementarity effect occurs when WFH generates new location-based activities. In this sense, WFH is associated with an increase in travel or more travel. Next, to saved commute time, increased flexibility in activity schedules may also be at the root of complementarity effects of WFH on travel (Mokhtarian, 1991b). Theoretically, constant travel time budgets (TTB) theory may explain complementary travel when working from home (Mokhtarian & Chen, 2004). According to the constant TTB theory, the average time dedicated to travel is about 60-75 minutes per individual per day measured over a sizeable amount of people (e.g. a nation) and a long time frame (e.g. a decade) (Mokhtarian & Chen, 2004). This means that less time spent on commute travel thanks to WFH or faster transportation does not lead to reduced time dedicated to travelling. Conversely, people eventually alter travel frequencies, destinations, or even residential choices or work locations (Mouratidis et al., 2021). Nevertheless, while this theory offers a theoretical explanation for potential complementarity, it is not regarded as absolutely true by literature (Mokhtarian & Chen, 2004).

Next, a modification (M) impact occurs when WFH neither reduces nor increases but modifies travel in other dimensions, such as travel modes, timing, activity sequences/routing and trip chaining. Furthermore, neutrality (N) occurs when WFH has no impact on other personal activities and related travel. An increase in WFH does not show any change in travel. Modification and neutrality are depicted in Figure 2.2 (3) (Andreev et al., 2010; Senbil & Kitamura, 2003).

After introducing the four types of interactions on a theoretical level, recent literature is reviewed to investigate current empirical findings.

2.3.3. Recent empirical studies on the interaction between WFH and travel

In earlier years, empirical studies continuously generated more or less consistent findings. They found that WFH substitutes and, thus, reduces travel in the short-term (Andreev et al., 2010; Mokhtarian, 1991b). Mokhtarian (1991b) analysed early research and concluded that WFH decreased commuting trips and other non-work trips do not increase, and relatively fewer peak travel trips are registered. Two decades later, Andreev et al. (2010) conducted another review of more than thirty articles. They also concluded that all studies discuss substitution effects. However, Elldér (2020) reviewed recent literature as a part of his study. He found a strikingly different picture compared to the earlier review studies (Andreev et al., 2010; Mokhtarian, 1991b). Almost all studies underpin the complementarity effects of WFH on travel.

As recent literature draws a more nuanced picture of the WFH and travel relation, literature from 2010-2022 is reviewed to investigate the relationship between dependent variables (travel modes and activity-travel), independent variables for WFH and relevant control variables. Table 2.3 below shows an overview of the review, for which Elldér (2020)'s study was an input for the years 2012-2018. In line with the objective of this research, selected articles focused on modes and activity-travel as dependent variables.

A crucial difference from earlier research is that more recent studies use high-quality data representative of larger national populations. Reasons for this may be twofold: WFH being more widely adopted but also WFH being included in many travel surveys (Elldér, 2020). Earlier WFH-travel studies were restricted to demonstration projects or sectors (Mokhtarian et al., 1995). However, an important difference is that earlier studies investigated changes in travel patterns for longitudinal data before and after people adopted working from home. This was not done in the more recent academic studies, shown in Table 2.3. All the studies in Table 2.3 used cross-section data. Given this insight, a few earlier studies are reviewed in Section 2.3.4.

The findings of the reviewed papers are discussed below, divided into total travel, activity-travel and travel per mode. While discussing the literature, the just introduced classification of SCMN is used as also done by Andreev et al. (2010) and Elldér (2020) to compare research results.

Total travel
Considering total travel, studies use different metrics: distances, e.g. VMT (vehicle miles travelled), PKT (person kilometres of travel), duration or trip rates.

A number of studies found that WFH people indicated more total travel, pointing towards complementarity (de Abreu e Silva & Melo, 2018; He & Hu, 2015; Zhu, 2012). More precisely, He and Hu (2015) found that WFH is positively associated with the total trip rates. Zhu (2012) found that frequently working from home is positively associated with distances travelled for all trip purposes. In contrast, Elldér (2020) found that full-day WFH people make fewer and shorter trips on WFH days. These findings point towards substitution. Travel demand is in parts offset by part-day WFH. Part-day WFH is associated with more trips and further distances. Elldér (2020) underpins with his findings the importance of differentiating between different WFH arrangements.

Activity-travel behaviour
Table 2.3 shows that studies investigating activity-travel differentiate at least between work and non-work travel. Again the studies use three different metrics: distances, duration and trip rates.
Depending on the purpose of the study, different levels of detail for activities were chosen, ranging from at least two (total work and non-work) (Zhu & Mason, 2014) up to 11 different purposes (Budnitz et al., 2020). Compared to others (Caldarola & Sorrell, 2022; Kim et al., 2015; Zhu, 2012), Budnitz et al. (2020) differentiated more purposes than only one or two main ones to gain more insight in the demand of trips for different purposes. However, diversifying only a small number of purposes already gives insight into behavioural patterns (Budnitz et al., 2020).

Table 2.3: General WFH and travel literature between 2010-2022, based on and extended from Elldér (2020)

Study	*Country*	*Data* [1]	*WFH variable(s)*	*G/D*[2]	*H/P*[3]	*Dependent variable(s)*	*Overall result*	*Models*
Travel by mode								
Ellder (2020)	Sweden	2011-2016 N=11,693 1-day trip diary	**Binary:** -Full day telework on survey day -Part day telework on survey day	D	P	-Any trip (binary) -Trips (total number) -PKT (total number) -VKT (total number) -Mode choice (categorical) -Rush-hour (binary)	**Substitution** Telework leads to reduced travel demand **Modification** Teleworkers travel more by active transport modes. Differences between full and part day teleworkers.	Different multivariate regression models
de Abreu e Silva and Melo (2018)	UK	2005–2012 single worker households N= 10,516 two-worker households N=6,803 7-day trip diary	**Ordinal:** Home-based telework frequency	G	H	-Travel distance and number of weekly trips by: -Car, -Active modes -Public transport	**Complementarity** Higher teleworking frequencies are associated with more travel (miles) by all modes, especially by car (only significantly for single-worker households.) Two-worker household, higher teleworking frequencies lead to more car trips but not more total household travel (miles).	Path analysis models, SEM
Lachapelle et al. (2018)	Canada	2005 N=5060 1-day time use diary	**Categorical:** -Working only from the workplace -Only from home -Combining home and workplace -Combining elsewhere -Home and/or workplace	D	P	-Total travel time -Walking/cycling 30 min or more -Departure time by motorized modes	**Substitution/ modification** -WFH full-day is positively related to less travel -WFH full-day is positively related to an increased likelihood of more than 30 min active travel	Different regression models
Ozbilen et al. (2021)	Puget Sound region, US	2017 N=3,430 respondents (from 2,385 households) 1-day and 7-day diary	**Continous:** Duration of teleworking (minutes)	G/D	P	Trip duration in minutes by: - Car - Public transport - Active modes	**Substitution** Respondents with higher telework durations tend to spend less time on car and transit	Tobit regression models
Activity Travel								
He and Hu (2015)	Chicago, USA	2007 N= 8883 1 and 2-day survey	**Categorical:** -Frequent -Infrequent -Non-telecommuters	G/D	P	Number of trips: -Total trips -Commute trips -Pick-up/drop-off trips -Maintenance/ discretionary trips	**Complementarity** Telecommuting positivly impacts the number of total trips, pick-up and drop-off trips, and maintenance/discretionary trips, while it is negative on commute trips.	Poisson regression, IV regression, MNL logit
Zhu (2012)	USA	2001 & 2009 1-day trip diary	**Binary:** -Frequent telecommuter -Non-telecommuter	G	P (H)	Distance, duration, and frequency of trips: -One-way commute -Total daily work trips* -Non-work trips**	**Complementarity** Telecommuting positively associated with workers' one-way commute trips (distance & duration), total work trips, and total non-work trips. Impacts are stronger in 2009 than in 2001.	IV approach, OLS, 2SLS
Budnitz et al. (2020)	UK	2002–2016 N=54,048 (32,940 households) 7-day diary	**Categorical:** -Once or twice a week -3 or more times a week -Non-telecommuters	G	P	11 work and non-mandatory trip purposes by trip rates:	**Complementarity/ Substitution** Telecommuters record fewer commute trips and more trips for other travel purposes.	MNL model
Asgari and Jin (2017)	New York, US	2010–2011 N=1,996 workers 24-h travel activity diary	**Categorical:** -Non-telecommuters -Full-day telecommuters -Part-day telecommuters	D/G	P	Five non-mandatory activities (in minutes) Shopping; Maintenance; Discretionary; Online Shopping; Escort	**Complementarity** (Full-day) Telecommuting is associated with decision to participate in non-mandatory activities	SEM
Travel by mode and Activity Travel								
Chakrabarti (2018)	USA	2009 N=108,697 1-day trip diaries	**Categorical:** -Frequent -Occasional -Non- teleworkers	D/G	P	-Number of walking and PT trips -walked/cylced >= 1 mile -30+ min of physical activity -VMT (miles on survey day & miles anually)	**Complementarity** Frequent and occasional teleworkers positively associated with most dependent variables	Different regression models
Kim et al. (2015)	Seoul, SK	2006 N=13,469 households one day trip diary	**Categorical:** -Telecommuter -Full-time office worker -Part-time office worker	G	H	PKT and VKT for : -Commute trip -Non-commute work trip -Non-work trip (e.g., pick up/drop off, education, shopping, leisure/visiting friends/recreation, other personal purposes)	**Complementarity** VKT: telecommuters' non-commute and non-work trips and his/her household members' non-work trips are higher than those of non-telecommuters and their household members. Teleworking partially reduces commute trips. Difference for household members only significant, if insufficient vehicles available.	Seemingly-unrelated censored regression (SUCR) model
Zhu and Mason (2014)	US	2001 & 2009 1-day trip diary	**Binary:** -Frequent telecommuter -Non-telecommuter	G	P (H)	VMT for: -Daily work trips* -Non-work trips**	**Complementarity** Telecommuters travel more VMT for total daily work, to/from work, related to business, and non-work trips compared to non-telecommuters The effect of telecommuting on worker's daily total VMT becomes stronger over time (2001 vs 2009).	IV Tobit models
Caldarola & Sorrell (2022)	UK	2005-2019 N=63,410 7-day diary	**Categorical:** -Non-teleworker -Medium-frequency -High-frequency	G	H	Travel distance and number of weekly trips by: -Car, -Active modes -Public transport & trips by purpose: -Commuting -Non-work -Total private (commute & non-work) -Business	**Complementarity & Substitution** Trips: Teleworker engage in more non-work trips and in total take fewer private trips (commute and non-work). Hence, avoided commute trips are more than compensated for by additional non-work trips. Distance: Majority of teleworkers (medium frq.) travel farther each week than non-teleworkers for private travel (commute & non-work), despite taking fewer trips and for business. **Tipping point:** If people telework three or more times per week, their weekly private travel is less than that of non-teleworkers.	Different econometric models

[1] All studies use cross-sectional data.
[2] General (G) or direct (D) indicator inidcating whether the respondent worked from home on the day of filling in the travel diary.
[3] Personal (P) or household (H) travel, H indicates that next to personal also travel of other household members was analysed.

*total daily work trips: incl. "to/from work" trips and "work-related business"
** non-work trips: (shopping trips, other family/personal business trips, school/church trips, medical/dental trips, visit friends/relatives trips, and other social/recreationaltrips

For work-related trips, existing literature differentiates between commute and business trips (Budnitz et al., 2020; Caldarola & Sorrell, 2022; Kim et al., 2015; Zhu & Mason, 2014; Zhu, 2012).

Budnitz et al. (2020) and He and Hu (2015) found results pointing towards complementarity: WFH is positively related to other trips (pick-up and drop-off trips, maintenance and discretionary trips) while they found a negative relation with commute trips. In line with these findings, Asgari and Jin (2017) showed that full-day WFH is associated with taking part in non-work activities, which supports the findings of Budnitz et al. (2020). Caldarola and Sorrell (2022) found that people working from home engage in more non-work trips but, in total, take fewer private trips (commute and non-work) than people not engaged in WFH. Thus, saved commute trips compensate for additional non-work trips (Caldarola & Sorrell, 2022).

Zhu and Mason (2014) found that daily work-related and other VMT are higher for frequent WFH people than for non-WFH people. Zhu (2012) found that frequently working from home increases one-way commute trips[5], total work trips and total non-work trips. Other studies also found that WFH is associated with increased commute duration or distance (de Vos et al., 2018). These findings lead back to the critical question of causality introduced in Section 2.3.1.
Caldarola and Sorrell (2022) find that people working from home travel further every week for what they define as private travel (commute and non-work trips) than people who do not work from home. They argue that these results stem from additional non-work trips and longer commutes. Still, they found that there appears to be a 'tipping point' if WFH three or more times (high-frequency teleworker). In that case, the weekly private travel is lower in the distance than that of other workers.

So far, the relation between WFH and business travel is not theoretically underpinned (Caldarola & Sorrell, 2022). Kim et al. (2015) found that WFH is partially associated with lower commute trips, however, WFH people's non-commute work trips (business) and non-work trips are higher. Next, Zhu and Mason (2014) and Caldarola and Sorrell (2022) also analysed non-commute work travel separately. Caldarola and Sorrell (2022) found that people working from home travel further for business per week than people who do not. By this, they confirm a strong association between WFH and business travel, also found by Zhu and Mason (2014). Budnitz et al. (2020) also included business trips. As mentioned before, they found that people working from home take more other trips and business trips explicitly included in these.

These results show that the complementarity or substitution perspective of results highly depends on the chosen travel metrics: distances, duration or frequencies. Still, considering trip purposes independently of the distance or duration allows uncovering whether individuals have trip budgets next to TTB (Budnitz et al., 2020; Mokhtarian & Chen, 2004).

Travel by mode
Several reviewed studies investigate the association of WFH with travel by modes. A number of studies inquired whether the use of active modes is reinforced when working from home (Caldarola & Sorrell, 2022; Chakrabarti, 2018; de Abreu e Silva & Melo, 2018; Elldér, 2020; Lachapelle et al., 2018; Ozbilen et al., 2021). These studies conclude that people who work from home make more use of active modes. However, the studies operationalise active travel very differently: frequency of trips, minutes, distance, differences in the definition can be seen in Table 2.3 in the dependent variables column. Also, the direct association of WFH is somewhat uncertain as only general indicators are often used. As indicated in Table 2.3 many studies use a general indicator for WFH frequencies, meaning it is not known if people indeed worked from home on the day of filling in the travel survey.

Lachapelle et al. (2018) show that important differences between distinct WFH arrangements exist. Chakrabarti (2018) find that full-day WFH appears to be positively associated with non-motorised travel and physical activities. They emphasise that high frequencies of WFH may lower PT demand. They underpin that full-day WFH people make significantly fewer miles but have a greater likelihood of active travel (> 30 minutes) on WFH days. Still, they also find that they make more miles annually than those

[5]One-way commute trips refer to one-way travel compared to merging to and from work travel. One-way commutes give direct indications about commute distance or duration, which is desirable if the association between commute distances and WFH frequency or status is studied.

who do not WFH. Frequently working from home (more than four times per month) is related to more weekly walking trips. Elldér (2020) confirmed these findings and showed that full-day WFH is associated with higher likeliness of active modes (walk or cycling). Here it is clear that the active modes are used for travel purposes other than commuting (because of full-day WFH). In the other studies, the purpose was unclear as the direct indicator misses or activities were not considered. Elldér (2020) also found that WFH people are less likely to make a car trip on WFH days than non-WFH people. Ozbilen et al. (2021) find that higher WFH frequencies lead to less time (duration) spent on car and PT. However, they did not report significant results for active modes.

de Abreu e Silva and Melo (2018) found that WFH is positively related to more miles by all modes (car, PT, AM) for single-worker households. This association is strong for the car, followed by active travel. They also analysed two-worker households and found that adults who WFH more frequently make more car trips. WFH has a positive but non-significant relation with total distance driven for two worker households. Thus, in spite of more car trips WFH does not lead to more total travel (distance) in a two-worker household.

Generally, the relation between travel modes and WFH is a somewhat understudied field, although some recent studies point towards a relation between WFH and active travel (Elldér, 2020). In all these studies, the association of WFH and travel modes are mostly studied separately, thus, the impact of WFH on all forms of travel is not analysed except by de Abreu e Silva and Melo (2018) who used a structural equation model.

Household members
Certain studies, marked in Table 2.3, studied household travel next to personal travel (Caldarola & Sorrell, 2022; de Abreu e Silva & Melo, 2018; Kim et al., 2015; Zhu & Mason, 2014; Zhu, 2012). Potential intra-household effects of WFH could be moving closer to the workplace of the non-WFH partner to reduce his or her commute. At the same time, WFH can change the task division between household members, which can impact travel modes or the amount of performed travel (de Abreu e Silva & Melo, 2018). For instance, de Abreu e Silva and Melo (2018) found that in one-worker households, WFH is positively associated with more miles by all modes. In comparison, for larger household sizes, only the higher miles by car remain significant. Also, Kim et al. (2015) found that other household members again offset some of the travel saved through WFH. Higher car availability for other household members may explain this effect (Kim et al., 2015). This confirms one of the hypotheses mentioned by Mokhtarian (1991b). Hence, WFH status of one person in the household may impact other household members' travel patterns, further complicating the relationship between WFH and travel behaviour.

2.3.4. Changes in WFH and travel behaviour

General
All more recent studies used cross-sectional data over several years, which does not allow to study changes in travel behaviour, except inter-temporal changes (Zhu & Mason, 2014; Zhu, 2012). The academic literature studying changes in WFH status and changes in travel behaviour are mostly limited to demonstration projects based on rather old and small datasets. These aspects limit the generalizability of their results (Kim et al., 2015). Insights into two major pilot projects are presented below. Other studies of a similar age exist as well, but these included telecenters, which are outside of the scope of this thesis.

Early projects which investigated changes in travel before and after adopting WFH, hence, a change in WFH status, found results pointing towards substitution. The two main insights are as follows (Kitamura et al., 1990; Hamer et al., 1991):

- Commute trips reduce in terms of trip rates when adopting home-based teleworking, WFH.
- Non-work trips do not show an increase but even a decrease, which could pinpoint to a tendency of chaining non-work activities to commuting (Mokhtarian, 1991b).

Multiple studies analysed data from a Californian Pilot Telecommuting Project, including roughly 200 state employees. The results show that on WFH days, people did not record any work trip and this did not lead to an increase in non-work trips for the worker or their household members (Andreev et al., 2010). The results of these studies show a 20 % decrease in total travel for poeple working from home in the travel diary period (Kitamura et al., 1990). More advanced analysis on the same dataset, with a sub-sample of respondents, showed a potential increase in non-work trips. Non-commute vehicle trips per day slightly increased on average while the vehicle distances decreased (Koenig et al., 1996). Pendyala et al. (1991) analysed the same dataset and additionally found that people working from home make proportionately fewer chained trips. Also, a shift in activities towards destinations closer to the home location was found on both WFH and non-WFH days, which can explain reductions in distances.

Hamer et al. (1991) analysed a Dutch pilot of 30 ministry employees and found significant reductions in the total number of trips, trips for different purposes (commute, business, others) and trips by different modes (car, PT, bicycle), on both workdays and weekends, and peak and off-peak hours. Significant reductions were also found in distances, but not as much as in trip rates.

While these studies deliver intra-personal insights, ICT has progressed since the 1990s, and the self-selection of participating in the pilot projects presents a limitation.

COVID-19

Only two articles were identified which studied the impact of WFH on travel in the COVID-19 context. Both studies only focused on people who were working from home during COVID-19.

Riggs (2020) used a retrospective survey to explore the travel before and after WFH mandates in the pandemic. Although distances decreased due to WFH and the stay-at-home advice, findings show an increase in total trips on average. Respondents reported that about 26 % of trips may have been induced by WFH. Hence they conclude that while vehicle distances may have decreased, trip rates and engine cold starts may have increased. They also found that active modes (walking and cycling) increased, primarily for social or recreational reasons, not for shopping. Shopping makes up a significant increase in driving related trips (Riggs, 2020).

Comparing these insights with a study from Italy, diverging insights are found. Campisi et al. (2022) investigated the impact of WFH on travel habits with a focus on walking and commuting pre and during the pandemic. They found that their respondents showed a propensity towards less walking, especially for leisure, even after the lockdown was lifted. This very different finding may be due to different national COVID-19 measures around the world. Campisi et al. (2022) explained the finding by possible fear of contagion which reduced travel overall. This explanation is strengthened by the finding that their respondents did not perceive the introduction of WFH as a factor that can lead to reduced walking trips in a homogeneous way. WFH can indeed lead to less walking trips related to home-work travel since walking to the workplace on a daily basis is replaced with WFH for most working days. However, it can contribute to increasing the walking frequency for leisure purposes. They found that people who no longer commute have a higher propensity to travel for leisure during the weekends compared to when they still commuted.

In both cases descriptive statistics were used and no actual longitudinal data or a travel diary. Besides this, findings from other countries based on COVID-19 data are difficult to compare. For instance, Italy or France, adopted lockdowns with strict travel limitations for non-essential activities whereas people in the Netherlands could still move around while social distancing (De Haas et al., 2020). People were encouraged to walk and cycle in the Netherlands.

2.3.5. Conclusions of the review and contribution

The reviewed literature informs about COVID-19 travel behaviour change, WFH before and during the pandemic and general WFH and travel literature. Concluding on the limitations and insights of these studies, the contribution of this research is emphasized.

Considering pre-COVID-19 studies, evidence of travel savings when working from home seems to be rather weak, especially if distances and duration are considered. Still, a relationship between different WFH arrangements and adopted travel patterns seems to exist. According to Caldarola and Sorrell (2022), travel patterns observed in the past fifteen years are not a good indicator for the future. The exogenous shock caused by the global COVID-19 pandemic led to drastic changes in working patterns. These changes make longer-term reductions in commute travel appear more likely. During the pandemic, more people adopted WFH on most days or full-time, as shown in Section 2.2.4. Furthermore, a considerable share expects to continue working from home when COVID-19 measures are lifted. This context in which many people switched to WFH and the availability of panel data may allow disentangling some of the effects introduced in the literature above by conducting a before and after study (Mouratidis et al., 2021).

The new fraction of WFH people who emerged during the pandemic are more diverse in terms of their lifestyles, socio-demographic and economic characteristics than people with WFH status pre-pandemic. They likely work from home several days a week, and for the short-term, they are less likely to have further commute distances than non-WFH people as relocation takes time. These new WFH people may adapt their activity-travel patterns differently to what was observed so far in general WFH and travel literature. During COVID-19, people were forced to work from home, whereas pre-pandemic people mostly self-selected to work from home, WFH was a choice. The sustainability of the newly adopted travel behaviour ultimately depends on the number of non-work trips, the chosen mode and the travelled distances for these trips (Caldarola & Sorrell, 2022).

Investigating the relation between WFH and travel patterns, a lack of accepted theory appears. As presented in the previous section, empirical research delivers very diverse findings (Andreev et al., 2010). Against this background, a study capturing the multitude of impacts WFH can have on different forms of travel (in terms of activities and modes) can provide valuable insights into more comprehensive behavioural patterns and adjustments. Studying simultaneous changes in trip frequencies per purpose and mode helps to uncover how individuals adapt or keep their trip budgets which allows understanding and assessing changes in activity-travel patterns when adopting WFH in a pandemic. The reviewed studies mostly analysed associations of WFH with single modes or single activities, but not simultaneous impacts. Next, no recent scientific study investigated changes in travel behaviour after adopting (or increasing) WFH. However, to effectively study the effect of developments in WFH on activity-travel behaviour, it is essential to study longitudinal data, which allows tracking changes over time. By this, notions of substitution, complementarity and modification can be analysed over time for the same people, which has not been attempted in recent years.

Next, the studies on COVID-19 travel behaviour change only studied aggregate trends. However, it remains to be uncovered whether the shifts in activity and mode shares are temporary or structural by continuously studying longitudinal data (De Haas et al., 2020). Intra-personal changes in activity-travel patterns after a change in WFH have not been studied in the COVID-19 context so far, although these may bring important insights into potential persisting structural changes. Against this background, disaggregate individual-level data analyses can show a clearer picture of trends in sub-groups of the population. Such analyses allow understanding the nature of the behavioural change, which remains hidden in aggregate analyses.

Against this background, this research contributes to studying the relationship between WFH and activity-travel behaviour during-and post- COVID-19 measures. Behaviour adopted during the measures should be studied, as it may or may not be predictive of future travel behaviour. Generally, travel behaviour is inert, and including this point in time may show whether COVID-19 was enough to disrupt habitual activity-travel patterns. In conclusion, this study combines two streams of literature and, thus, contributes to general WFH and travel and post-pandemic travel behaviour research.

2.4. Conceptualisation

The previous sections describe what literature discusses about COVID-19 travel behaviour change, the adoption of WFH during COVID-19 in the Netherlands, and the impact of WFH on travel in general. COVID-19 was a natural 'experiment' in which a lot of people changed to WFH or increased their WFH intensity, as shown in Section 2.2.4. Still, it remains unknow how a change in the WFH status or frequency (may it be an increase or decrease) during the pandemic relates to changes in different activity-travel patterns for the working population in the Netherlands. The availability of longitudinal data and the COVID-19 context allows to study such changes.

COVID-19 travel behaviour change and general WFH and travel literature report about the relationship of WFH or COVID-19 with mode use and activity-travel. Considering similar associations or effects discussed by both literature bodies, a conceptual model for this research is created, depicted in Figure 2.3.

The building blocks of this conceptual model are a change in WFH status, commute travel, other non-work travel, mode use, individual characteristics and COVID-19 measures. In this research, commute travel, non-work travel and mode use together define **activity-travel patterns**.

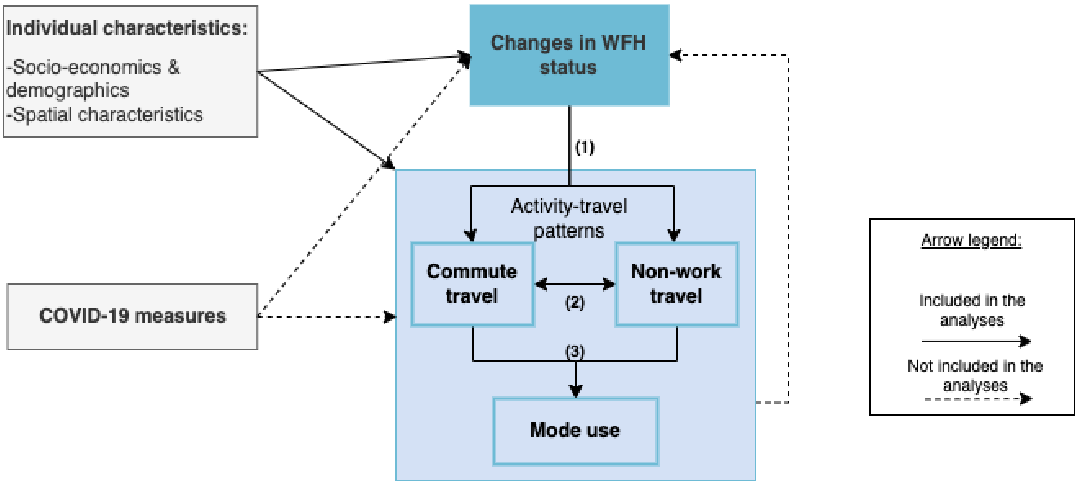


Figure 2.3: Conceptual model

The conceptual model synthesizes three important relationships from literature. First, WFH has an impact on travel activities: commute travel and other non-work travel (1). Next, the relationship between activities themselves, commute and non-work travel is included (2). Furthermore, an indirect relationship between WFH and mode use (3) running trough activities is depicted.

An impact of WFH on activities (1,2)

To shed light on the relationship between a change in WFH and activities, commute trips and non-work trips are included in the conceptual model to assess the impact of stimulating WFH.

Divided fronts exist in research for the relationship between WFH and activity-travel, notably between commute trips and non-work trips. Some studies found results purely pointing towards substitution, while more recent studies find complementary results or both substitution and complementarity effects of WFH on activity-travel. Replacing working at the workplace with WFH leads to a reduction and, thus, substitution in commute trips (1). However, due to saved time on commute trips, the absent commute trips may generate new location-based non-work travel (2). Theoretically, complementarity effects, detected in numerous studies, for more non-work travel by people working from home may partly be explained by constant travel time budgets. Thus, time saved on commute travel may be used for other non-work trips. Next, increased flexibility in scheduling may also lead to increased non-work travel (1). Still, it can be assumed that not all people necessarily show the same behaviour. This is in line with the theory of constant TTB [6], as this notion rather holds at population level. Nonetheless, also at

[6] In the COVID-19 context, with increased WFH levels, constant TTB may also mean that people who did not adopt or increase

population level this theory is disputed (Mokhtarian & Chen, 2004). Besides complementarity effects, some people who increase their WFH frequency may only substitute the work trip and keep similar non-work trips. Additionally, a substitution in commute trips and non-work trips is also possible. For instance, Elldér (2020) found that WFH is associated with a lower trip demand. Similarly, early literature also found substitutions in both commute and non-work travel after adopting WFH (Hamer et al., 1991; Kitamura et al., 1990). Substitutions in non-work travel when working from home may be due to the fact that workers often chain non-work trips to commute trips. These explanations underpin that different relationships between a change in WFH and activity-travel are possible. COVID-19 travel behaviour change literature reported similar changes in activities as general WFH literature. Decreases in commute travel appeared because many people did not commute to work anymore. However, outside activities such as roundtrips gained in popularity in the Netherlands, which points towards increases in non-work, leisure travel (De Haas et al., 2020).

In the conceptual model, working trips purely refer to commute trips, to/from work travel. Certain studies reviewed in Section 2.3.3 also included **business travel**. However, when included, business travel was listed as a separate variable and not mixed up with commute travel. The reason for this separation is a lack of theory on the relationship between business travel and WFH (Caldarola & Sorrell, 2022). While WFH may lead to more other trips due to saved time on commuting or more spatio-temporal freedom, business trips likely do not have the same effect. Business trips are usually done during working hours (Hamersma et al., 2021). Thus, business travel is not included in the conceptual model.

An impact of WFH on mode use (3)

In COVID-19 travel behaviour change and general WFH and travel literature, a connection between mode use and activities can be synthesised, depicted in Figure 2.3 (3). Individual modes, such as active modes and the car, gained in popularity while PT became less popular during COVID-19. The loss in popularity of PT is closely related to the WFH policies (De Haas et al., 2020; Hamersma et al., 2020). Notably, PT, which is predominantly used for commuting in the working population, decreased while AM for recreational purposes increased. This shows that the mode and the travel purpose share a relation (3). COVID-19 research shows that working trips are rather done by PT or car and recreational trips are increasingly done by AM when working from home for large parts of the population (Riggs, 2020). At the same time general WFH and travel literature also showed a relation between the use of modes and WFH. Such research mostly studied the association between WFH and modes, but this relationship is likely linked to activity-travel behaviour. Thus, the conceptual model only shows an indirect effect of WFH on mode use running through activities (3). Elldér (2020) showed that full-time WFH, so days without commute trips, were positively associated with active mode use (Elldér, 2020). He proposed as a possible explanation that the available time when working from home encourages the use of slow modes. Since, this relation is found for full-day WFH, defined as a day without commutes, this active travel is per definition linked to non-work travel. Ozbilen et al. (2021) found that higher WFH frequencies lead to less time (duration) spent on car and PT, which are often used for commute travel. Also, Chakrabarti (2018) found that full-day WFH appears to have a positive association with non-motorized travel and physical activities. Certain studies also underpinned a positive association of WFH and the number of car trips. Summarizing the insights of COVID-19 travel behaviour change and general WFH and travel literature, it is apparent that mostly three modes, car, PT, and AM (walking and cycling) are investigated. Thus, these three modes are also the input for this research. However, as stated in Section 2.3.5 simultaneous changes on these dimensions have not been studied yet.

In conclusion, people seem to adopt different activity-travel patterns, defined by travel purposes and modes, once they work from home. The explanations above underpin the conceptual relations that this research assumes between WFH and activity-travel in Figure 2.3.

Causal assumption

As seen in Section 2.3.1, general WFH and travel literature is uncertain about the causal direction between WFH and activity-travel patterns. Given the studied context, COVID-19, the causal assumption

WFH started travelling more due to less congestion and crowding.

is taken that a change in the WFH status has an impact on changes in activity-travel, but at the same time previous activity-travel patterns also have an impact on future activity-travel patterns[7]. The direction of causality discussed in general WFH and travel literature was more concerned with self-selection and the residential and work location, and, thus, the commute distance and how this relates to adopting WFH or not. According to the impacts introduced in Section 2.3, this is a rather long-term change and, hence, not part of the scope of this thesis. During COVID-19, the adoption of WFH was motivated by an external shock and governmental measures. Hence, this bi-directional relationship does not hold in this context.

The only bi-directional relation which may hold is depicted by a dotted line in Figure 2.3. Hamersma et al. (2020) indicated that public transport users were strongly affected. People who commuted by PT prior the pandemic were more likely to increase or uptake WFH. This is conceptually a challenging relationship as it means that pre-COVID-19 travel patterns influenced the adoption of WFH. Thus, WFH could not be considered as fully exogenous to travel behaviour. Nonetheless, for simplicity, it is assumed that WFH is fully exogenous to activity-travel in this context.

Next, individual characteristics are also important to consider when studying the effect of WFH on activity-travel patterns.

Individual characteristics

Socio-demographic and economic characteristics and spatial variables are important to include, as these impact the ability and adoption to WFH but also activity-travel patterns. A change in WFH during COVID-19 is, as explained in Section 2.2.3, mediated by a number of these characteristics. Furthermore, the studies reviewed in Section 2.3.3 all controlled for individual characteristics and found multiple variables to be significant. Thus, individual characteristics are added to the conceptual model. Table A.1 in Appendix A summarizes personal and spatial variables used as control variables by the reviewed studies, serving as an input for the operationalisation in Chapter 4.

COVID-19 measures

The last aspect which influences both WFH and activity-travel are COVID-19 measures which are exogenous. However, these measures can be considered a constant at each time point as they were at a national level and, thus, held for everybody.

All aspects discussed above form the basic conceptual model for this research. The relationships shown by dotted lines are not further considered in this research. Chapter 3 and 4 elaborate in more detail how the relationships, shown in this conceptual model, are studied in this research.

With regard to the research, certain general phenomena are expected to be seen based on the reviewed literature. Based on distinct findings in literature, it is expected that heterogeneous commuter groups exist pre-COVID and that depending on their initial activity-travel patterns they adopt different patterns when a change in WFH occurs. Against this background, mixed results of complementarity, substitution, neutrality and modification when a change in WFH occurs are expected. The approach chosen in this research, introduced in Chapter 3, allows to uncover whether diverse findings exist in the sample. Next, due to COVID-19 measures, generally lower PT levels are expected for WFH and non-WFH people.

Next, in case of an increase in WFH, it is naturally expected that people reduce their commute trips by all modes and more diverse effects for other non-work trips by all modes may exist, such as:

- A considerable number of people may adopt patterns with many active trips for non-work travel. General literature and COVID-19 literature assume a relationship between WFH and active mode use (Riggs, 2020; De Haas et al., 2020).

[7] This relationship is not depicted in the conceptual model in Figure 2.3.

- General WFH and travel literature also found that people who work from home take more car trips for non-work purposes (de Abreu e Silva & Melo, 2018). Thus, this effect may also exist for certain people.
- General reductions in mobility during COVID-19 and findings by Campisi et al. (2022) make high shares of low mobility when working from home also expectable. This is in line with reductions in commute and non-work travel when adopting working from home found by early longitudinal research (Hamer et al., 1991; Pendyala et al., 1991).
- In line with what COVID-19 showed, it is expected to see reduced levels for PT usage for people who adopted working from home. It is expected that the trend of reduced PT usage is stronger for people who started/ increased working from home than for non-WFH people. Ozbilen et al. (2021) found that higher WFH frequencies lead to less time (duration) spent on car and PT, and thus, on commute modes.

While careful expectations are formulated, it is assumed that also so far undiscussed effects may appear as people were forced to WFH while pre-COVID-19, WFH was marked by self-selection. This underpins an exploratory side of the research at hand.

This research also investigates a post-COVID-19 measures time point. It is expected that the WFH extent does not decrease as much as it increased initially during COVID-19. Many employees expect to continue working from home for a few days per week post measures. Against this background, it is expected that shares in activity-travel patterns are redistributed given certain lasting experiences or created habits during COVID-19. Thus, a potential short-term structural effect of WFH (and COVID-19) on travel patterns may exist.

3

Methodology and data

This chapter presents the methodology and the data used in this research. First, the method choice and steps are explained and critically assessed in Section 3.1. Second, the data and measures are presented in Section 3.2. In this section, the Dutch Mobility Panel (MPN), its variables, the wave and respondent selection are discussed. Third, the chapter finishes with the sample composition and representativeness in Section 3.3.

3.1. Method choice and method steps

3.1.1. Method choice

Considering the objective of this research, the chosen approach must be able to study longitudinal panel data to investigate intra-personal changes in activity-travel patterns after a change in WFH. Furthermore, simultaneous changes on multiple indicators must be allowed to uncover potential substitution, complementarity, modification or neutrality at a personal level.

In transport research at minimum two approaches to study panel data exist (Kroesen, 2014). The first one usually includes structural equation modelling with lagged stability and cross-lagged relationships over time. In this approach, variables are directly related over time (Golob, 2003). This line of research generally concludes that the past is predictive of future travel behaviour, and thus, finds travel behaviour to be rather inert (Kroesen, 2014). Indirect and direct effects can be studied with this method and it allows to deal with complex structures. However, this method cannot reveal much about the exact nature of change that occurs in the data. Conclusions are only drawn based on averaged effects, revealing a main trend.

Another less adopted approach assumes that at each time point, a finite number of classes underlies the associations between the variables in focus and changes over time are modelled by transitions between these classes (Kroesen, 2014). This approach exists under different names, such as Latent Transition Analysis (LTA) or Markov Models. Compared to the first approach, no lagged relationships between variables are estimated. In this second approach, the assumption holds that effects over time are conveyed by latent class variables, whose definition based on observed indicators remains the same over all points in time. Additionally, this approach allows to study effects of exogenous variables on initial class membership and on the transition probabilities between points in time (Kroesen, 2014).

A recent selection of literature deployed LTA to investigate the impact of life events on changes in travel patterns in the Netherlands (De Haas et al., 2018; Kroesen, 2014). Important to note is that also here it is assumed that past travel patterns influence future travel patterns. Thus, this literature applies a clustering method, as belonging to a certain cluster can impact the likelihood of changing to another cluster in the next time-point, while also an event can impact this change. De Haas et al. (2020) indicated that this lens may be a suitable perspective to study changes in travel patterns during COVID-19. Clustering methods allow to model simultaneous changes on multiple indicators which is in line with the methodological requirements of this research.

This study takes an approach inspired by the just mentioned research, which was rooted in the mobility biographies framework, literature investigating travel behaviour change when life events occur (De Haas et al., 2018). Against, this background, the changes in WFH are conceptualized as an event, an exogenous variable, which interacts with transitions. The aim is to isolate the impact of changes in WFH during COVID-19 on transitions in activity-travel patterns.

3.1.2. Latent transition analysis model

The LTA model outlines transitions among latent categorical variables, captured by a measurement model (Nylund, 2007). Nylund (2007) introduced several analysis steps for building a LTA model to ensure meaningful and accurate results. These steps are adapted to the research at and hand which encompasses two main steps inspired by Olde Kalter et al. (2020): *1. Assessment of the optimal number of classes, 2. Specification of the LTA.* Both steps are conducted using the software package Latent Gold (Vermunt & Magidson, 2013). For the first step, **Latent Class Models** are estimated and for the second step **Latent Transition Models**. The remainder of this subsection characterizes the methodological design and discusses advantages and limitations.

1. Assessment of the optimal number of classes

1.1 Estimation of several measurement models and model selection: First of all, existing activity-travel patterns are identified by estimating different measurement models and selecting the best model. **Latent Class Analysis (LCA)** is chosen to find meaningful patterns as it is the most common measurement model for LTA applications. It is a natural choice, as the LTA is often described as the longitudinal extension of a LCA (Nylund, 2007). LCA has several advantages over traditional clustering techniques (e.g. K-means) to understand behaviour based on holistic profiles. The three most crucial advantages are as follows (Vermunt & Magidson, 2002): First, mixed scale types can be used for variables. This is an important advantage as in this study the indicators are trip rates which are count variables, whereas covariates take on different scale types. Second, research units are not deterministically assigned but probabilistically, which reduces classification bias. Deterministic assignment means research units get assigned to one single class, which leads to problems if the research units do not belong to any cluster in a very clear sense. LCA overcomes this drawback by a probabilistic assignment to clusters, a probability of belonging to each cluster. Third, statistical criteria help support the choice of the most appropriate class model (Vermunt & Magidson, 2002). Fourth, while exogenous variables are often used for the description of distinctions between clusters, the LCA accounts for these variables in the class assignment process. Here a distinction is made between active and inactive covariates. Active covariates can be included to predict class membership whereas inactive covariate can be included for the description of differences between classes (Vermunt & Magidson, 2016).

A conceptual model of the LCA, including the terms used above, is depicted in Figure 3.1. The model notably consists of indicators, covariates, and the latent classes, which are activity-travel patterns in this research. As indicated in Chapter 1, one of the contributions of this work is the simultaneous consideration of trips by mode and purpose to define activity-travel patterns. Three transport modes car, PT and AM and two generic trip purposes: commute trips and trips for other non-work travel are included for the reasons mentioned in Section 2.4. Three types of modes and two purposes lead together to a set of six distinct indicators, which describe trips by different modes and purposes: to/from work trips by car, to/from work trips by PT, to/from work trips by AM, other trips by car, other trips by PT, other trips by AM. Thus, the latent variable presents a respondent's activity-travel pattern. The measurement model in the top part of Figure 3.1 illustrates these assumptions. Covariates are not illustrated as these are discussed in more depth in the model operationalisation in Section 4.3.

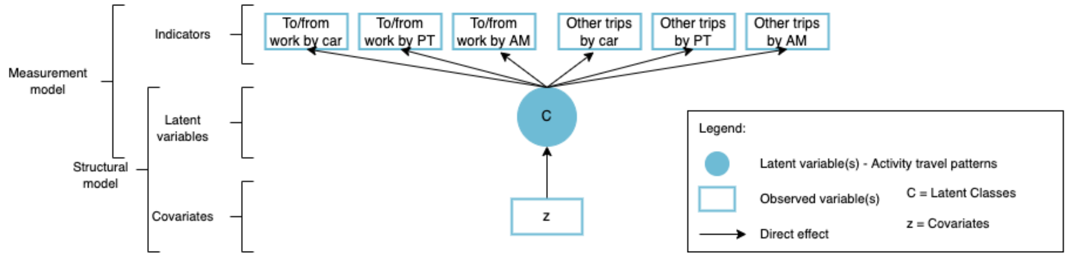


Figure 3.1: Latent class analysis model - conceptual model, adapted from Nylund (2007)

The identification of activity-travel patterns across different points in time requires selecting the optimal number of latent classes first. In line with the approach by De Haas et al. (2018), data of multiple time points is used simultaneously to estimate the latent class model. Hence, measurement invariance is assumed. The Wald test statistic is used to verify whether indicators are indeed significant and, hence, strongly differentiate between clusters. Measurement models ranging from 1-10 classes are estimated to select the best class solution. Different statistics exist to assess the appropriateness of the number of latent classes, next to considering the interpretability of results (Magidson & Vermunt, 2004).

Magidson and Vermunt (2004) elaborate on three methods to select a class model:

1. First, the L^2 can be used. L^2 indicates the maximum likelihood chi-square test which compares observed frequencies with model-estimated ones. However, as the indicators are the number of trips per purpose and per mode many different response patterns exist in the sample. Hence, a multitude of patterns have an observed frequency of zero. Thus, the chi-square test should not be used in this case, as based on this test all models would be rejected.
2. Second, the Bayesian Information Criterion (BIC) can be used to select a class model. In this case, the class model with the lowest BIC is the most suitable for the data. This criterion accounts for model fit (LL) and parsimony (number of parameters).
3. Third, a method that is statistically less precise than the first two exists. The L^2 of the 1-class model may be used as a baseline of the overall amount of association in the data. When contrasting the L^2 of models with more classes with the baseline, the reduction presents the overall association explained by the model. Once the additional reduction of L^2 becomes relatively small, the inclusion of an additional class is no longer justified (De Haas et al., 2018). Both Kroesen (2014) and De Haas et al. (2018), used this method to select the class model.

To ensure that the local fit is also satisfactory next to the global fit, the Bivariate Residuals (BVR) should also be examined. The residuals represent estimates of the improvement in model fit (LL) when a direct effect between indicators is accounted for (Magidson & Vermunt, 2004). The BVRs are chi-square distributed, and thus, values above 3.84[1] (df=1) stipulate that the local fit is not adequate and significant residual association remains which is not explained by the clusters (Ton et al., 2022).

Nonetheless, statistical criteria need to be evaluated in conjunction with interpretability. A class model with adequate statistics is not useful if it is theoretically nonsense. Hence, next to the statistical criteria, the interpretability of classes and the class sizes need consideration. Previously, LCA researchers indicated that classes should not be smaller than 5% [2] (Weller et al., 2020).
Thus, in this research the class-model, the optimal number of activity-travel patterns, is selected based on the BVR, the BIC, the reduction of L^2 and the interpretability and meaningfulness of the classes.

1.2 Inclusion of covariates in the measurement model: Once the best class model is selected active and inactive covariates are added to the measurement model. The Wald test statistics indicate whether covariates significantly affect initial class membership. Validity support is reached if covariates meaningfully refer to the measurement model, based on theory (Nylund, 2007). Only necessary covariates should be included to keep the model parsimonious and interpretable.

[1] As a rule of thumb the value 4 is also often used (Magidson et al., 2020).

[2] Nevertheless, such assumptions have been relaxed in the past. In these cases, researchers must assess whether small classes make sense conceptually and they must consider the sample size (Weller et al., 2020).

2. LTA model estimation
After identifying activity-travel patterns, transitions between classes are evaluated by extending the model to a transition model.

The LTA model output consists of three sets of parameters and their associated means (or probabilities). These are the initial state probabilities (t=0), the transition probabilities between t-1 and t (t>0) and a state specific distribution of the indicators (Vermunt & Magidson, 2016). These parameters are used to compute transition matrices, showing transition probabilities. Transition probabilities express the probability of transitioning to an activity-travel pattern in the subsequent wave, given a respondent's membership in an activity-travel pattern in the first wave (Nylund, 2007). Thus, initial activity-travel patterns also influence the transition probabilities. The inclusion of covariates, allows to evaluate the effect of a change in WFH on these transitions. By this, LTA allows evaluating if people with distinct activity-travel patterns are differently affected by a change (increase or decrease) in WFH. It is crucial to differentiate between two kinds of covariates: time-constant and time-varying covariates in the LTA (Nylund, 2007). Time-constant covariates can interact with both the initial state[3] probabilities and the transition probabilities, while, time-varying covariates can only interact with transition probabilities. An example of a time-constant covariate is for instance gender, while a change in WFH hours is a time varying covariate.

Different matrices can be computed, the average transition matrix, averaged over all covariate levels, but also matrices for the occurrence of a certain covariate level. The latter allow studying the effect of a change in WFH on transitions in more detail.

Time itself is an important time-varying covariate. Models in which transition probabilities vary across time, are defined by adding time as a covariate influencing the transition probabilities (Vermunt & Magidson, 2016).

Nonetheless, the LCA and the LTA bear certain limitations.

Limitations LCA
As the LCA forms the basis of the main method, the LTA, certain limitations have to be acknowledged. A first drawback is that large sample sizes are needed to estimate parameters appropriately (Kroesen, 2014). Still, no hard rules about the sample size exist (Weller et al., 2020). This drawback can be faced by the availability of the relatively large datasets from the MPN. Second, another drawback of the method is the assumption of local independence of indicators (Magidson et al., 2020). As the indicators in this research present individual trip rates of respondents, some correlation between indicators eventually remains, which limits the model validity. In general, this assumption regularly needs to be relaxed in real world cases. Third, the LCA can only account for a limited number of indicators to produce meaningful clusters in a parsimonious model. Thus, a selection of independent and meaningful indicators must be made. In turn, other important indicators may be excluded. For instance, in this research trips, by other modes are left out.

Limitations LTA
Also the use of LTA comes with certain limitations. The assumed measurement invariance condition presents a first limitation for this study. The abrupt COVID-19 situation may have generally changed travel patterns which makes an assumption of full invariance debatable. Still, assuming measurement invariance brings interpretability benefits and it does not necessarily lead to a wrong model but simply to less flexibility in fitting the data. Next, all covariates are at the same level in the causal chain in the LTA. Thus, no indirect effects between covariates can be estimated. For instance, indirect effects of individual characteristics running through WFH on travel may be interesting but these cannot be studied with a LTA. Nonetheless, adding covariates that interact with the transitions rapidly increases the number of estimated parameters which may lead to convergence problems. Thus, the transition model should purely focus on the effect of WFH, which is in the center of this study, and not on other individual characteristics. Furthermore, the LTA has limited 'memory', since only first-order effects are considered in this research (Nylund, 2007). Finally, large sample sizes present another drawback.

[3] In LTA classes are referred to as states.

Sufficient cases are needed to test effects on transitions in a LTA. However, as a change in the WFH extent is considered as the exogenous variable that interacts with transitions, and this was induced by national policy, enough cases probably show these changes. Thus, smaller sample sizes than those deployed by Kroesen (2014) and De Haas et al. (2018) are likely acceptable.

3.1.3. Critical assessment of method choice

With regard to the ideal conceptual model presented at the end of Chapter 2 in Figure 2.3, conceptual challenges need critical assessment against the chosen method. Two aspects need to be discussed, conceptual loss and the impact on outcomes or conclusions that can be drawn.

Section 2.4 reveals that personal characteristics and pre-COVID travel mode influence the adoption of WFH pre-and during-COVID. Section 2.2.3 showed that pre-COVID public transport users were more prone to adopt WFH. This leads to a conceptual loss in the sense that WFH is not an endogenous variable here but fully exogenous. Hence, reverse effects marked in Figure 2.3 and indirect effects of individual characteristics are not studied in this research. Nonetheless, as WFH was a measure enforced by the government, it is still justifiable to assume an exogenous effect but the results need to be interpreted with care. Ignoring endogeneity and COVID-19 measures, the effects of a change in WFH on activity-travel patterns may be slightly overestimated, leading to biased findings.

While these assumptions have a critical impact on outcomes, a possible effect of a change in WFH can still be studied. An attempt to isolate the effect of a change in WFH is made by including all working people not only those who work from home. This allows to analyse how people who experience a change in WFH change activity-travel patterns compared to those who do not by analysing transition matrices for the occurrence of a changes in WFH or no change. Next, COVID-19 may amplify some of the effects of WFH. However, the COVID-19 measures depicted in Figure 2.3 were at a national level. Thus, while these measures certainly influence activity-travel behaviour, they can be assumed to be normally distributed in the population and present a constant at every measurement point for everybody. Still, COVID-19 impacts are expected to be seen when comparing average results from one year to another, especially for non-WFH people.

3.2. Data and measures

To study a potential impact of changes in WFH on transitions in activity-travel patterns via LTA, longitudinal data is required. The present research deploys data from a longitudinal data collection effort of the Dutch Mobility Panel (MPN) (KiM, n.d.). The Netherlands Institute for Transport Policy Analysis (KiM) initiated the MPN in 2013.

3.2.1. The MPN

With the MPN, the KiM collects data on the travel behavior of a fixed group of people and their households over multiple years. This mobility panel provides insight into the factors that impact changes in the travel behavior of the Dutch population. Moving, having children, changing jobs, buying a new vehicle, these events and many more have an effect on the way people move. The panel also provides insight into the mobility of different groups of people, e.g. young people, people with children or families, or the elderly, working or unemployed (KiM, n.d.). By this the MPN is suitable to study how changes in people's lives affect mobility.

Respondents aged 12 and older from approximately 2,000 complete households record their mobility behavior in a 3-day travel diary. Respondents get assigned three consecutive days during the survey period to fill in the diary. The weekdays assigned to a respondent remain the same for every repeated measurement. In the diary, respondents indicate all their movements, trip characteristics, delays, parking costs and travel companions. Next to the diary, the respondents complete different questionnaires that provide in-depth background information about themselves and/ or their households (KiM, n.d.).

Due to the pandemic, the KiM conducted special corona measurements in addition to the yearly measurement. In contrast to the regular September-November waves, the COVID-19 waves are at a personal level and not at a household level. The COVID-19 measurements are naturally focused on the pandemic and accordingly only travel diary data and one questionnaire containing data on the working or studying situation, experiences and perceptions related to these, or COVID-19 in general are included. Still, regular and corona MPN measurements include extensive information on how people travel (modes, trips purposes, distances, travel times etc.) and the amount worked from home, at the workplace or elsewhere.

Hoogendoorn-Lanser et al. (2015) give more information about the MPN and design choices.

General panel data limitations

Although panel data presents many advantages, it also has disadvantages. As panels are relatively expensive and time-consuming they are often rather small. Consequently, certain changes in WFH may have a rather low observed frequency. In consequence, certain levels of a change in WFH can eventually not be studied. Another commonly acknowledged drawback is panel mortality. This means that with each measurement certain respondents quit in a sense that they do not fill in the survey anymore. This must be kept in mind when choosing a sample. Only including respondents present at each measurement occasion may bias the data and the representativeness of the sample. Thus, this study chooses respondents who are present in two consecutive waves. Nonetheless, the general panel sample size and panel mortality limit the maximal sample size that can be obtained in this research.

MPN limitations for this study

The use of MPN data has certain limitations for this study. Generally, a multiple day, here three-day, travel diary offers advantages over one-day travel surveys conducted in Sweden or the United States, as alternations in travel patterns can be recorded (Caldarola & Sorrell, 2022). The UK uses a week-long travel survey (Budnitz et al., 2020; de Abreu e Silva & Melo, 2018). Still, it needs to be acknowledged that respondents get assigned three consecutive days during the survey period to fill in the travel diary. These days remain the same for every measurement. However, this also means that certain people fill in the diary on weekend days which is a major limitation of the MPN data for the research at hand. Respondents who filled in the diary on weekend days could be taken out, but this would only leave in cases which started filling in the diary on a Monday, Tuesday or Wednesday. This would reduce the sample to less than half of its size. Hence, it is decided to include an active covariate for reported weekend days in the LCA and LTA to control for these days, see Section 4.3. Finally, the personal level of the corona measurements limits the study of WFH effects on the travel of other household members. More limitations are discussed while operationalising the change in WFH variable in Chapter 4.

3.2.2. Variables in the MPN

The MPN data is already cleaned to some extent. Still, to conduct the attempted analyses the data needs further preparation. As the scope of this research is set to personal daily mobility in the Netherlands, occupational[4], vacation trips or other trips abroad are excluded from the datasets. This is in line with the data preparation of the Mobiliteitsbeeld by the KiM.

The following paragraphs explain the variables in the MPN and choices made for this research. Limitations and consequences of choices are discussed as well.

Activity-travel variables

As already introduced in Section 2.4, only two activity types are distinguished: commute trips and trips for other purposes. In the MPN, activities can be derived from trip purposes. The purpose of a trip corresponds to the destination of the trip, except if the destination is home. If the destination is home, the purpose corresponds to the origin. It is not referred to work trips, as a work trip still leaves room for interpretation. A work trip can be a commute trip or refer to all work-related trips (incl. business travel). The studies reviewed in Section 2.3.3 all referred to commute trips. Some studies also included business travel, however, they did not mix commute and business travel. In the MPN the definition coming closest to a commute trip are trips with the purpose *'to and from work'*. This includes trips originating from home and ending at the fixed workplace, but also trips originating from another place,

[4]Occupational trips are trips related to certain occupation types, such as being a truck or bus driver.

for instance from school after dropping of a child. Next to this, trips from work to home directly are also included. Trips from work to any other destination such as the grocery store are labelled by the corresponding purpose e.g. *'Shopping, doing grocery shopping'* and thus, are considered *'other trips'* for non-work purposes. Trips for work purposes which do not go to a usual workplace as destination, are called 'business-related visit in work context' in the MPN. For instance, locations visited to meet a client fall into this category. Figure 3.2 summarizes the definition of trip purposes based on destinations in the MPN. As argued in Section 2.4, business travel is not studied in this research. Table 3.1 shows which trip purposes are included in *'other trips'*.

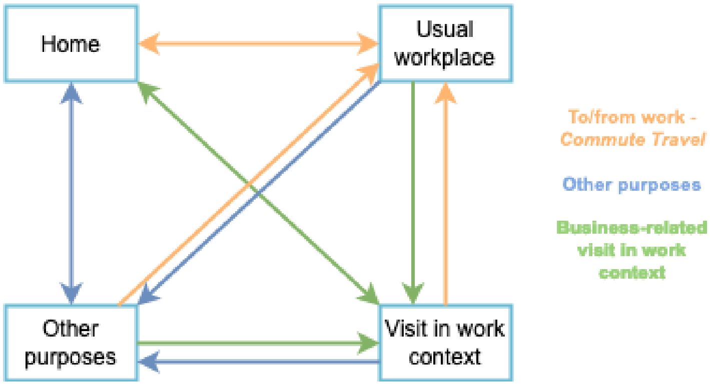


Figure 3.2: MPN trip purposes based on origin and destination, adapted from Crawford (2020)

As reasoned in Section 2.4, three mode categories are distinguished: car, PT, and AM. Table 3.2 shows what each category includes. The modes refer to the main modes used for a trip in case a multi-modal trip was recorded.

Table 3.1: Trip purposes

	Trip Purposes
To/from work	To and from work
Other trips	Services, personal care
	Shopping, doing grocery shopping
	Following education study, courses
	Visitation
	Social recreational other
	Touring, hiking
	Other purpose
	Unknown
Business travel	Business-related visit in work context

Table 3.2: Trip modes

	Transport Modes
Car	Car as driver
	Car as passenger
PT	Train
	Bus/tram/metro
AM	Bicycle
	Walking
Others	Scooter/ Moped
	Other

Two **limitations** are apparent considering the two included purposes and the three included modes, which together lead to six indicators for the LCA and LTA:

1. Trips by other modes for both purposes are not included.
2. Business-related visits in work contexts by all modes are not included.

Business trips could be merged with commute trips (to/from work). However, Section 2.3.3 showed that WFH has a different impact on commute trips than on business trips. Thus, commute trips and business trips should not be merged. WFH was positively associated with business trips, while it was negatively associated with commute trips in existing studies. Including business trips separately leads to three additional indicators, which makes the model less parsimonious. As mentioned in the limitations of the LCA choices about indicators need to be made.
Other modes could also be included but these would also add two additional indicators, and thus, make the models less parsimonious. Existing LTA studies on mobility patterns also did not include other modes (Kroesen, 2014; De Haas et al., 2018). Leaving out these trips would lead to an overestimation of others patterns if respondents only used other modes. Similar effects could appear for business travel. Nonetheless, business travel only accounts for 1.8 % of all trips, and trips by other

modes for 2.5 % as depicted in Table 3.3 and Table 3.4 [5]. Thus, as these trips represent extreme low shares it is defensible to exclude them in a trade-off for model interpretability and parsimony.
To investigate whether the existence of these trips biases class membership, business trips and trips by other modes are added as inactive covariates to the LCA.

Table 3.3: Trip rates by purpose for 2019

	Trip rates	Percent
To/from work	6786	29.5%
Other trips	15830	68.7%
Business	413	1.8%
Total	23029	100%

Table 3.4: Trip rates by mode for 2019

	Trip rates	Percent
Car	12964	56.3%
PT	1052	4.6%
AM	8444	36.7%
Others	569	2.5%
Total	23029	100%

WFH variables
The extent of WFH is directly measured by asking respondents about the hours they worked from home in a recent week on a continuous scale. Hence, changes in WFH can be computed based on changes in the extent of WFH between two subsequent time points. This procedure is document in Section 4.2.

This variable bears three **limitations**. The formulation of 'recent week' in the MPN is quite ambiguous, because it is unknown how much a respondent worked in the week of filling in the travel diary. Next, this formulation is also prone to include many overtime hours, as it does not refer to contract hours. Furthermore, this variable refers to working from home in general. It does not distinguish between actual home-based teleworkers and home-based workers. For this reason, this research simply refers to WFH and not teleworking. Finally, only the number of hours worked from home are known and not the days per week, as in existing studies. These drawbacks need to be accepted as it is an existing dataset.

3.2.3. MPN wave selection

Since the sub-sample for the special COVID-19 measurements is drawn from the 2018 panel, data ranging from 2018-2022 can be used for this study. The sample size of the additional COVID-19 measurements are smaller compared to the regular waves as only a sub-sample is drawn. Thus, choosing an additional COVID-19 measurement leads to a reduced sample size. This presents a drawback as LTA and LCA require large sample sizes. Initial data analyses find that selecting COVID-19 measurements reduces the sample size by at least half compared to using regular MPN waves.

Figure 3.3 illustrates the general COVID-19 situation at each measurement wave. In this figure, the September-October waves depict regular yearly measurements, whereas all others are additional COVID-19 measurements.

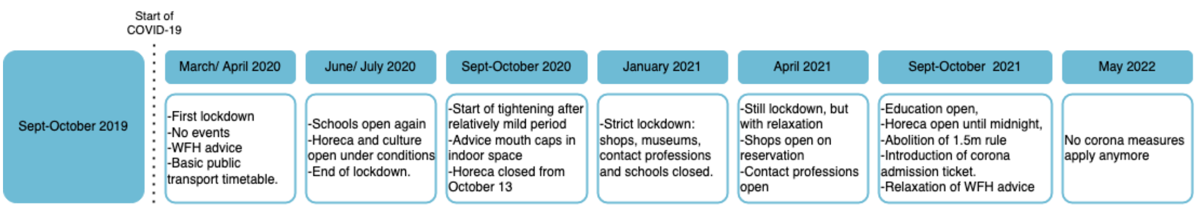


Figure 3.3: COVID-19 measures at MPN measurement points,adapted from De Haas and Faber (2022)

The choice for the pre-COVID-19 wave is relatively straightforward: the most recent wave is chosen, September 2019. May 2022 is selected for the post COVID-measures time point, because restrictions got lifted in March 2022, as shown in Table 3.5. A consequence of this choice is that for the post-

[5] Both tables show the total number of trips for 2019 based on the respondent selection presented in Section 3.2.4.

measures wave the sample is remarkably smaller. This consequence is discussed in Chapter 4.

Table 3.5: Tightening and relaxation of WFH Advice

Date		WFH rules
2020		
6th March	**T**	Advice to WFH if possible
12th March	**T**	WFH as much as possible
1st July	**R**	End of intelligent lockdown
18th August	**T**	Tightening WFH advice
29th September	**T**	WFH unless not possible
2021		
26th June	**R**	WFH advice relaxed to 50/50 at home and office
19th July 2021	**T**	WFH unless not possible
24th September	**R**	Relaxation of WFH advice: WFH if possible, at the office allowed if necessary
3rd November	**T**	WFH at least half of the time
12th November	**T**	WFH, only go to work if needed
2022		
15th February	**R**	Working from workplace half of the time
15th March	**R**	No more corona rules and no longer advice to WFH

T=Tightening; **R**=Relaxation

Choice for during-COVID wave
The choice for a during-COVID-19 measures wave is less straightforward. Initial COVID-19 waves such as March 2020 can also deliver insights. However, these waves may lead to extreme initial COVID-19 effects and at the same time these waves halve the sample size. Hence, to keep the sample size at a maximum only regular waves (September 2020 and 2021) are considered to select a during-COVID wave.

To make a choice between September 2020 and 2021, the WFH and the general COVID-19-situation are compared.

- **WFH situation:** In September 2020, more people were working from home full-time compared to September 2021. In September 2021, certain people likely already found their hybrid optimum. Still, the WFH levels were considerably higher in September 2021 than pre-COVID which becomes apparent in Figure 3.4 in Section 3.3.
  Although the WFH levels in September 2021 are lower, this wave likely draws a more truthful picture for the post-COVID situation because throughout the pandemic some people stopped WFH, as revealed in Section 2.2.4. The people who were still working from home in 2021, are more likely to also do so after the pandemic for a few days per week. Thus, the insights gained can inform post-pandemic consequences of WFH on travel more truthfully.
- **COVID-19 situation:** Considering the general COVID-19 situation, September 2020 was more severe than September 2021. As summarized in Figure 3.3, September 2020 was a period where the Netherlands went into lockdown on October 13th, halfway trough the MPN. Starting from this date Horeca was closed and events were forbidden.
  In September 2021, the situation around recreational and social activities was remarkably different. Horeca was open until midnight and most other activities were possible with a COVID-19 admission ticket. Only in the last four days of the MPN, November 12th, a lockdown was introduced. However, during this lockdown everything remained open at first, only the COVID-19 admission ticket was required for more activities and closing hours got adapted.
  As total closures for many social activities are assumed to weigh heavily on trips for non-work purposes, the less strict September 2021 wave is also here preferred.

Generally September 2020, was a moment of tightening measures and WFH was required unless not possible. Stricter COVID-19 measures in September 2020 could bias the observed transitions severely given more severe restrictions at that time leading to an overestimation of WFH effects. 2021 was a situation where all activities were open and WFH was highly encouraged but people could already go back to work for about half of the time. This underpins that 2021 is slightly closer to a post-pandemic scenario.

In conclusion, the September 2019, September 2021, and May 2022 waves are selected for this study. Nonetheless, the May 2022 dataset bears the limitation of a significantly smaller sample size.

3.2.4. Respondent selection

In line with Sullivan (2003), this research adopts a project-specific definition of WFH. General WFH and travel studies excluded people with home-based occupations, without fixed workplaces or without any commute tips[6], or only identified people with teleworkable jobs as teleworkers.

It is assumed that changes in WFH during COVID-19 are mostly made by people who worked at a work location before and transitioned to working from home. This is in line with the traditional definition of telework which stipulates that the work can be done from a workplace and if at home ICT is used, see Section 2.2.2. However, since it cannot be excluded that other workers may be included as well, the broader term: working from home is used instead of telework.

Although Section 2.3.3 showed that household travel is also prominently studied when investigating impacts of WFH on travel, the unit of analysis in this study are individual workers and their personal daily mobility in the Netherlands. The rationale, behind this choice is, as indicated in Section 3.2.1, that the COVID-19 measurements of the MPN are only at a personal level.

Two COVID-19 studies which also investigated the impact of changes in the WFH status on travel behaviour in the pandemic, only analysed the people who indeed worked from home (Riggs, 2020; Campisi et al., 2022). However, this research purposefully includes all workers as this allows to isolate the effect a change in WFH may have on transitions between travel patterns during COVID-19. People who did not work from home likely also changed their activity-travel patterns due to COVID-19. By including also these respondents without a change in WFH, it can be identified whether there is an additional effect of a change in WFH on activity-travel patterns besides the effect of other COVID-19 measures. Hence, the sample is formed by the Dutch working population.

These individuals are selected in several steps listed below:

1. Only respondents which completed both the 3-day travel diary and the personal questionnaire(s) are selected. The diary contains activity-travel data and the personal questionnaire the WFH data, thus, both are required.
2. Next, since this research investigates the effect of a change in WFH on personal mobility in the Netherlands, only workers are considered. This decision is in line with all articles reviewed in Section 2.3.3.
3. In line with the previous step, and the definition given in Section 2.2.2 only people working for pay are included. In the MPN working is rather broad definition. To effectively only include people working for pay, the most applicable work situation of a person is considered. The following working people are included: self-employed entrepreneur, employed non-governmental job, employed by the government. Whereas the following are excluded as they likely do not work for pay: occupational disability/ unfit to work, unemployed/searching for a job/on social welfare, retired or taken early retirement, studying, schooling, internship, housewife/houseman/other, volunteer work. Self-employed workers are included. Although literature discusses potential ambiguous effects of these workers, multiple articles reviewed in Section 2.3.3 included them as well, while carefully listing them. This research does the same.
4. In line with the definition by the Centraal Bureau voor de Statistiek (CBS), only people working at least 12 hours could be considered as workers. However, as the MPN data is used in this research, reports by the KiM have been analysed and these included all working people not only

[6] Excluding people without any commute trips would be problematic, as many people adopted WFH full-time during COVID-19.

those working more than 12 hours (Hamersma et al., 2020). Thus, this research also includes all working people as long as they worked for at least one hour. Respondents which indicate 0 working hours are filtered out even though they indicate that they work. This could for instance be the case for respondents who in theory have a working contract but their workplace was closed or similar. Still, this leads to large differences in the number of working hours, which likely also influences commute and non-work travel. Thus, working hours are included as an active covariate in the LCA.

5. Finally, since transitions are studied, only respondents present in two consecutive waves are selected.

The following section presents the sample descriptives.

3.3. Descriptive statistics

As described in the previous section, only respondents present at two consecutive waves between 2019, 2021, and 2022 are selected. This leads to a total sample of 1829 respondents. 1774 respondents were present in 2019 and 2021, 726 in 2021 and 2022, and 671 in all three waves.

To inform about the general sample composition, active and inactive covariates are depicted in Table 3.6. For 2022, all individual characteristics are imputed from 2021 as this information is not collected in COVID-19 MPN measurements.

Table 3.6: Sample composition

		Wave pair 2019-2021		Wave pair 2021-2022	
		2019	2021	2021	2022
To/from work car trips in 3 days	Mean (SD)	1.5 (1.9)	1.1 (1.7)	1.2 (1.8)	1.2 (1.8)
To/from work PT trips in 3 days	Mean (SD)	0.3 (0.9)	0.1 (0.6)	0.1 (0.6)	0.2 (0.7)
To/from work AM trips in 3 days	Mean (SD)	0.7 (1.6)	0.6 (1.4)	0.7 (1.5)	0.8 (1.5)
Other car trips in 3 days	Mean (SD)	3.3 (3.7)	2.7 (3.4)	2.4 (3.3)	2.2 (3.1)
Other PT trips in 3 days	Mean (SD)	0.2 (0.6)	0.1 (0.4)	0.1 (0.5)	0.1 (0.5)
Other AM trips in 3 days	Mean (SD)	2.4 (3.2)	2.4 (3.1)	2.4 (3.0)	2.6 (3.3)
Age	Mean (SD)	44.1 (11.4)	46.1 (11.4)	45.4 (11.8)	46.4 (11.8)
Working hours per week	Mean (SD)	34.9 (9.4)	34.4 (8.9)	33.9 (8.7)	33.7 (8.9)
WFH hours per week	Mean (SD)	3.3 (7.2)	9.9 (13.2)	9.3 (13.1)	8.3 (11.7)
Most applicable work situation (%)	Self-employed entrepreneur	7.3	7.5	9.1	8.7
	Employed non-governmental job	73.7	74.1	75.8	75.8
	Employed by the government	19.0	18.4	15.2	15.6
Sector (%)	Healthcare	19.0	20.1	20.4	*idem 2021*
	(Retail) trade	7.7	7.9	9.6	*idem 2021*
	Automation and IT	7.9	7.5	6.2	*idem 2021*
	Education and science	11.2	11.7	9.2	*idem 2021*
	Industry and production	7.7	8.2	8.7	*idem 2021*
	Public administration, security and justice	5.7	7.2	5.6	*idem 2021*
	Financial services	6.3	5.9	6.2	*idem 2021*
	Others	34.6	31.6	34	*idem 2021*
Education level (%)	Low	13.5	13.4	16.4	*idem 2021*
	Medium	38.6	38.5	43.7	*idem 2021*
	High	47.9	48.1	39.9	*idem 2021*
Personal income (%)	<500-1500 €/month	11.2	7.4	10.9	*idem 2021*
	1501-2500 €/month	35.8	30.4	30.4	*idem 2021*
	2501-3500 €/month	31.2	36.5	35.1	*idem 2021*
	>3501 €/month	8.2	11.9	11	*idem 2021*
	Unknown	13.6	13.8	12.5	*idem 2021*
Gender (%)	Male	48.9	48.9	51	*idem 2021*
	Female	51.1	51.1	49	*idem 2021*
Family Cylce (%)	Single	22.0	21.6	23.8	*idem 2021*
	Adult household	44.9	46.5	45.9	*idem 2021*
	Household with a youngest child with the age ≤ 12	25.3	24.9	21.3	*idem 2021*
	Household with a youngest child with the age of 13 up to 17	7.8	6.9	9	*idem 2021*
Level of urbanization (%)	Urban, >1500 inhabitant/km^2	54.3	56.4	58.4	*idem 2021*
	Sub-urban, 1000-1500 inhabitant/km^2	17.9	14.7	14	*idem 2021*
	Rural, <1000 inhabitant/km^2	27.8	28.9	27.5	*idem 2021*
Car license (%)	No	4.6	4.3	5.8	*idem 2021*
	Yes	95.4	95.7	94.2	*idem 2021*
Car (%)	0	11.6	9.5	13.4	*idem 2021*
	1	86.4	87.0	83.7	*idem 2021*
	2	1.0	2.5	2.2	*idem 2021*
	4	1.1	1.0	0.7	*idem 2021*
Reported weekend days (%)	0	41.4	41.4	43.4	*idem 2021*
	1	26.5	26.5	30.6	*idem 2021*
	2	32.1	32.1	26	*idem 2021*
Change in WFH	Hours				
Decrease (%)	32+		0.2		0.6
	24-31		0.2		0.6
	16-23		0.4		2.5
	8-15		2.1		9.9
	1-7		8.5		11.2
No change (%)	0		46.4		59.1
Increase (%)	1-7		8.3		10.1
	8-15		10.3		4.3
	16-23		9.7		1.1
	24-31		7.6		0.6
	32+		6.3		0.3

WFH levels
The development in working from home levels between the three years is briefly discussed below.

Figure 3.4 shows the distribution of respondents by the number of hours worked from home in a recent week in all three years. The identified trends between 2019 and 2021 are well aligned with what Dutch COVID-19 WFH studies found, presented in Section 2.2.4. Especially the three categories with higher WFH hour counts (+16 hours) saw a substantial increase from 2019 to 2021, shown in Figure 3.4. The share of people who did not work from home at all fell from 64 % in 2019 to 50 % in 2021 in the sample. Also, in the two subsequent categories a decrease appeared. However, this decrease in shares is likely due to shifts to categories with higher WFH frequencies.

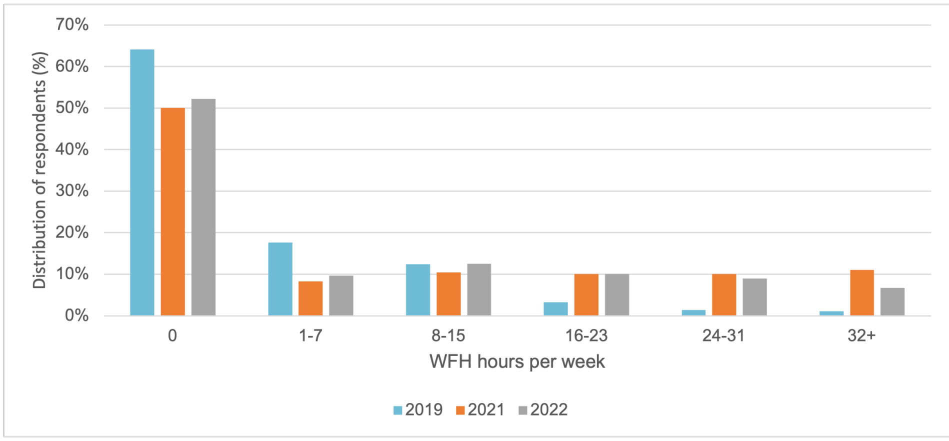


Figure 3.4: Developments in WFH levels 2019-2021-2022

In March 2022 the Dutch government lifted all COVID-19 measures, including the recommendation or advice to work from home. Hence, since March 2022, WFH has not been a policy measure anymore. Figure 3.4 shows that some movement in both directions, increases and decreases in the shares, are standing out. While the share of people working 16-23 hours per week from home remained fairly constant, the shares of the three lower categories slightly increased. The shares of the two highest categories decreased. Especially in the 32+ category, a decrease in the share emerges. Still, compared to the pre-COVID-19 levels in 2019 the share of people working from home full-time is substantially higher. Increases in shares of the lower categories in 2022, likely represent respondents who shifted from working from home (almost) full-time to a lower extent.

It needs to be acknowledged that only about 7 months lie in-between the figures shown for 2021 and 2022. Hence, decreases may be less extreme as businesses and people may still be in a transition phase, or structural increases in WFH remain. As discussed in Section 2.2.4, the share of people working from home decreased over the course of the pandemic in 2020, while a significant proportion (40 to 60 %) of WFH people expected to work more from home when the pandemic ends. The proportion of people expecting to work from home more increased from March 2020-September 2020. This may be due to fewer people continuing working from home over time. People who no longer work from home anymore are less likely to continue WFH after the pandemic and are also not asked in the survey anymore (Hamersma et al., 2020, De Haas et al., 2021). These aspects may explain a certain stability around WFH levels in the data.

Sample representativeness
Table 3.6 depicts the characteristics of the workers in the study sample. However, to generalise the study results to the Dutch working population, the selected sample should be representative of this population. To assess the representativeness of the sample, data of the Dutch working population provided by Statistics Netherlands (CBS) is used (CBS, 2022). CBS defines the working population, as the employed labour force. According to CBS, individuals with paid work, living in the Netherlands, independently of the working hours, form this population. The presented data usually concerns people between 15 and 74 years (CBS, 2022). This definition partially aligns with the sample selection of this

study, differences are discussed in Appendix B.

The sample representativeness, including the presentation of variables and limitations due to data availability and CBS definitions are discussed in more depth in Appendix B. Since both wave pairs, 2019-2021 and 2021-2022, include the year 2021, 2021 sample data is compared to CBS data from 2021, presented in Table 3.7.

Table 3.7: Sample representativeness

		Wave pair 2019-2021 (2021)	Wave pair 2021-2022 (2021)	CBS (2021)
Working hours per week (%)	Part-time (less than 35 hours)	42.6	44.2	48.1
	Full-time (35 hours or more)	57.4	55.8	51.9
Most applicable work situation (%)	Self-employed entrepreneur	7.5	9.1	15.6
	Employed non-governmental job	74.1	75.8	84.4*
	Employed by the government	18.4	15.2	-
Gender (%)	Male	48.9	51	52.8
	Female	51.1	49	47.2
Education level (%)	Low	13.4	16.4	19.4
	Medium	38.5	43.7	39.2
	High	48.1	39.9	40.8
	Unknown	/	/	0.6
Age (%)	Up to 24 years	1.5	3.6	16.4
	25-34 years	17	17.5	21.1
	35-54 years	51.8	50.6	41.0
	55-64 years	26.9	26.3	18.4
	65+	2.8	2.1	3.0
				CBS (2020)
WFH (%)	Not WFH	50	53.2	59.0
	WFH	50	46.8	41.0

*No distinction between being employed for governmental or non-governmental job

All things considered, the sample provides an acceptable picture of the Dutch working population, except for a severe underrepresentation of people aged up to 24 years compared to CBS data. Differences in the statistics between the study samples and CBS data most likely stem from differences in the definition of the working population. This research samples on the most applicable working situation, as explained in Section 3.2.4. In consequence, people who indicate to be a student as their most applicable working situation are not included in the sample, although many work part-time. CBS likely includes working students in their data. This problem could be avoided by also sampling on secondary working situations next to the most applicable work situation.

Nonetheless, no statistical tests are required to conclude that the sample is not entirely representative of the Dutch working population, given small variations on almost all variables. Next to slight differences in the definition of the working population, further variations could also be due to differences in variable definitions and the longitudinal design of this research. Due to panel mortality, people drop out from one year to another. Respondents are only included if present in two consecutive wave pairs. Thus, although the MPN is a representative panel, the sample in this study is not fully representative. The fact that the sample is not entirely representative presents a limitation that needs to be acknowledged when assessing the results.

4

Model operationalisation

This chapter elaborates on the model operationalisation. First, indicators are operationalised in Section 4.1. Second, changes in WFH are studied descriptively to operationalise change in WFH variables in Section 4.2. Third, the inclusion of other exogenous variables is discussed in Section 4.3. Finally, this chapter concludes with visualizing the operational models of this research in Section 4.4.

4.1. Indicators

Section 2.3.3 showed that studies use different metrics to operationalise total travel, activity-travel and travel by mode. While distances are interesting to deduce sustainability insights in terms of CO2 emissions, research shows that distances and duration are eventually biased because of rounding errors in the self-reported diary (Rietveld, 2001). In this sense, trip rates are supposedly a more precisely self-reported indicator (De Haas et al., 2018). Nonetheless, distances should still be added as inactive covariates to gain additional information on how far certain classes travel.

Thus, trip rates by purpose and mode are operationalised and used as indicators for the activity-travel patterns. Three types of modes and two purposes lead together to a set of six distinct indicators, which describe trip rates by different modes and purposes: to/from work trips by car, to/from work trips by PT, to/from work trips by AM, other trips by car, other trips by PT, other trips by AM. The trip rates represent count variables, which can only take on zero or positive integer values (Kroesen, 2014).

Based on the scale of a variable a distribution needs to be assumed for the indicators in Latent Gold. Count variables can be modelled by a Poisson or a binomial distribution in Latent Gold (Vermunt & Magidson, 2016). Given that the count variable represent trips rates it is obvious that a Poisson distribution is selected, as this one is not limited in outcomes. Hence, for each cluster in the model the estimation of a Poisson rate is given (Vermunt & Magidson, 2016).

4.2. Change in WFH variable

To study the effect of a change in WFH on activity-travel patterns, a variable capturing the change in WFH is required. The studies reviewed in Section 2.3.3 all considered the WFH frequency as an independent (or endogenous) variable in their cross-sectional studies. The WFH indicators used by these studies can still inform the operationalisation of a change in WFH variable for this study.

The MPN has four measures available to explore changes in the extent people work: the hours worked, the hours WFH, the hours worked from the workplace and the hours worked from somewhere else in a recent week. Thus, compared to other travel surveys, WFH is not indicated in days per week or per month in the MPN, but in hours in a recent week on a continuous scale.

As introduced in Chapter 1 and Section 3.2.3, three time points, pre-, during- and post-COVID-19 measures, are selected to study transitions. Initial data analyses, based on absolute changes in WFH hours, reveal that for 2019-2021 only few people have a decrease in WFH (see Table 4.1) and if so additional analyses show that this is related to working less in general. Thus, including a decrease variable for 2019-2021 does not make sense based on the data. For 2021-2022, the frequencies for an increase are rather low, but the decrease frequencies show potential to study the effect of a decrease in WFH.

Rational for model operationalisation
For parsimony reasons it is decided to operationalise and estimate two LTA models. This has certain advantages and disadvantages compared to a LTA model including three time points, and thus, two transition moments. As the contexts and time intervals between waves are very different, a model with heterogeneous transition probabilities would have been required (Nylund, 2007). Thus, time would be an additional nominal covariate to interact with transitions and, thus, account for heterogeneous transitions over time (Vermunt & Magidson, 2016). However, this would lead to a large increase in parameters just to account for an effect of time. Considering the small sample size of wave pairs for 2021-2022 (N=726) this quickly leads to high parameter estimates for the last time point due to low frequencies of certain transitions.

Next, the occurrence of decreases is rather low for 2019-2021 and the same holds for increases in 2021-2022. For parsimony reasons, the 2019-2021 parameters to estimate decreases can be saved by merging a decrease in WFH with no change in WFH cases and the same procedure holds for 2021-2022 for an increase in WFH. This makes the transition matrices more reliable as no conclusions are drawn based on matrices with only a handful of cases. For instance, if a decrease is defined as a decrease in WFH if equal or larger than 8 hours per week, only 51 cases show such a decrease for 2019-2021, Table 4.1. Using 51 observations for a transition matrix with 49 cells, given a 7-state LTA[1], would deliver very unreliable results. A drawback of estimating two models is that the activity-travel patterns may slightly change and more reporting effort is required. Weighing off model parsimony and reporting effort, it is decided to estimate two distinct transition models which allow to study effects of a change in WFH more clearly. Hence, the effect of an increase is studied for 2019-2021, and the effect of a decrease for 2021-2022.

Table 4.1: Change in WFH 2019-2021 and 2021-2022

		Change in WFH hours 2019-2021 (N=1774)		**Change in WFH hours 2021-2022 (N=726)**	
	Hours	Frequency	Percentage	Frequency	Percentage
Decrease	32+	4	0.2%	4	1%
	24-31	3	0.2%	4	1%
	16-23	7	0.4%	18	2%
	8-15	37	2.1%	72	10%
	1-7	150	8.5%	81	11%
No change	0	827	46.6%	429	59%
Increase	1-7	147	8.3%	73	10%
	8-15	182	10.3%	31	4%
	16-23	172	9.7%	8	1%
	24-31	134	7.6%	4	1%
	32+	111	6.3%	2	0%

4.2.1. 2019-2021: Increase in WFH variable

This subsection lays out the operationalisation of an increase in WFH variable which is included in the transition model for 2019-2021. To operationalise a variable for an increase in WFH, arguments based on empirical and theoretical insights, policy relevance, and descriptive data analyses are considered.

Theoretical and empirical insights:
While several studies defined WFH once per week as frequently working from home, three of the reviewed existing studies differentiated between WFH 1-2 days and 3 days or more (Budnitz et al.,

[1]The next chapter reveals that 7 activity-travel patterns should be used in the LTA.

2020; Caldarola & Sorrell, 2022; de Abreu e Silva & Melo, 2018). Here Caldarola and Sorrell (2022) strikingly found a tipping point that when people work from home 3 or more times per week, they start reducing their private travel [2] compared to people who do not work from home. People who work from home once or twice per week travel further than people who do not work from home for private travel although they take fewer trips. They found that a combination of longer commutes and additional non-work travel leads to more registered travel for people who work from home 1-2 days per week [3].

Policy relevance
The majority of employees expect to work from home for 1-3 days, and only 10 % expect to continue working from home full-time after the pandemic ends (Hamersma et al., 2020). In 2021, the KiM reported an expected average increase of 1-2 days WFH per week compared to pre-COVID (Hamersma et al., 2021). Hence, investigating a change in WFH at different WFH levels is particularly interesting form a policy perspective.

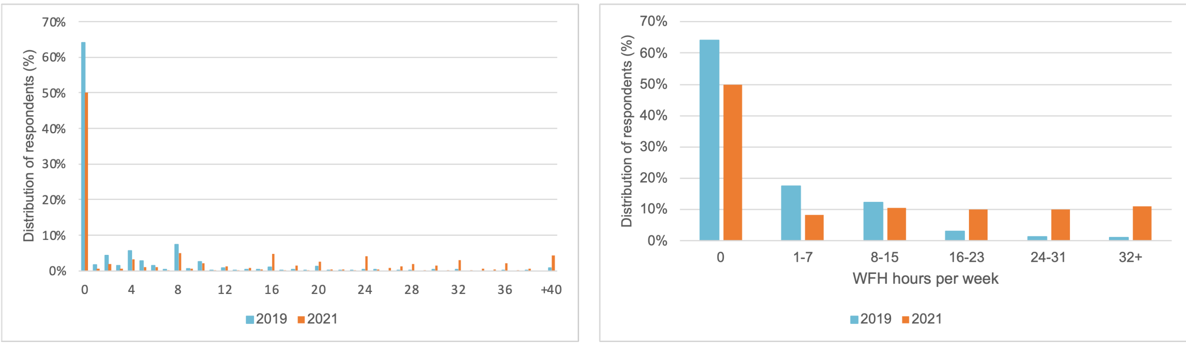
Taking the theoretical insights and the policy relevance into consideration, studying the difference between an increase of 1-2 days and 3 or more days allows to gain insights for a future post pandemic. The following investigates the MPN data to operationalise such change levels.

Descriptive data analyses
The change in WFH (in hours per week) is received by subtracting the hours worked from home in 2021 with the hours of 2019, as depicted in Equation 4.1. Meaningful changes at hour-level per week are used to operationalise a change in WFH variable.

$$WFH_t - WFH_{t-1} = \Delta WFH \tag{4.1}$$

The absolute change in WFH hours is chosen over a relative change in WFH hours. Compared to a relative change, the absolute change in WFH hours gives an idea about what the change in WFH may mean in terms of working days. This is desirable to conclude on relevant effects for policy-makers. The result indicates the absolute change in hours for each respondent on a continuous scale. However, the change in WFH likely does not have a linear effect on activity-travel patterns. Hence, the raw delta in WFH hours, as a continuous variable, is not used as a change in WFH variable for the transition analysis.

Figure 4.1 shows the development of the WFH level between 2019 and 2021. Clear jumps at counts of 8 stand out for 2021 in Figure 4.1 (1), this may indicate that many people increased WFH by full working days of 8 hours.



(1) (2)

Figure 4.1: WFH development between 2019-2021

Plotting the same graph for a positive delta (increase) in WFH, a very similar pattern appears in Figure 4.2. This indicates that WFH and a change in WFH are likely highly correlated. At the same time, this

[2]Caldarola and Sorrell (2022) defined private travel as the combination of commute trips and non-work travel, thus, excluding business travel.
[3]Caldarola and Sorrell (2022) measured travel in distance per week

points towards mostly increases in full WFH days. Still, this is a before-after study and to test the impact of a change, the delta in WFH is further analysed and not the WFH extent.

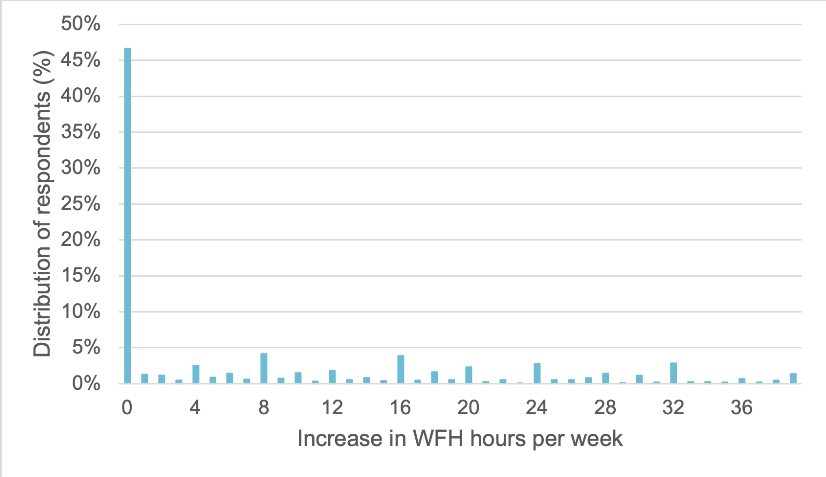


Figure 4.2: WFH increase in hours per week between 2019-2021

Table 4.2 below shows in counts of 8 hours the frequency and percentage of respondents per changes in WFH for 2019-2021. It stands out that the share of respondents with a slight decrease in WFH and a slight increase (less than 8 hours) are rather similar. Such fluctuations may be traced back to increases or decreases in overtime or similar, especially as the share in both directions is similarly high. These minor fluctuations likely do not have an impact on transitions between activity-travel patterns. As the increase or decrease is then less than a common working day, such cases are classified as no change in WFH as they assumably have a similar impact. Thus, for the subsequent analyses an increase or decrease is only defined as such if equal or higher than 8 hours per week. This is in line with previous literature. The review of recent general WFH and travel studies showed that many studies use WFH one day per week to classify people as frequently working from home (Chakrabarti, 2018; He & Hu, 2015; Zhu & Mason, 2014; Zhu, 2012).

Based on the distributions, differentiating between a small increase by 8-23 hours and a large increase by more than 24 hours seems promising. As indicated, a decrease is not further investigated given the very low frequency counts for 2019-2021.
An ordinal scale is chosen instead of a continuous one as the results in previous literature were so diverse that no linear effect of different increases in WFH levels is assumed. As an ordinal scale is chosen, more than two increase levels are not considered to keep the model parsimonious. This leads to three levels:

- **No increase:** Representing no change in WFH, an increase or decrease of less than 8 hours and all other decreases. All other decreases are added as these are likely drawn back to a change in the overall working situation and not solely a change in WFH.
- **Small increase in WFH:** Representing an increase by 8-23 hours per week (probably in many cases one up to three days per week).
- **Large increase in WFH:** Representing an increase by at least 24 hours per week (probably in many cases at least three days per week).

These three levels allow to create two dummy variables to interact with the transitions between activity-travel patterns for 2019-2021.
The WFH level in 2021[4] and the increase in WFH on an ordinal scale are highly correlated r=0.875, indicating a very strong relationship. Surely, already pre-COVID-19 a minority worked from home full-time or for a couple of hours per week, but this research is explicitly focused on the effect of a change in WFH. People who already worked from home may not have changed their activity-travel patterns as much or they changed them differently.

[4]On an ordinal scale of 0:0-7 hours; 1:8-23 hours; 2:+24 hours WFH per week

Table 4.2: Changes in WFH hours per week between 2019 and 2021

	Change in WFH hours 2019-2021 (N=1774)	Frequency	Percentage
Decrease	32+	4	0%
	24-31	3	0%
	16-23	7	0%
	8-15	37	2%
	1-7	150	8%
No change	0	827	47%
	1-7	147	8%
Increase	8-15	182	10%
	16-23	172	10%
	24-31	134	8%
	32+	111	6%

The variable definition has certain limitations:

- The WFH variable comes in hours per week in the MPN this can also include working overtime at home. Hence, WFH does not always mean that people go less often to the workplace and, thus, actually reduce commute travel. Working overtime at home has other travel impacts than WFH for full working days from home (Mokhtarian, 2021). It is partly tried to face this limitation by not including changes in WFH levels which are less than 8 hours per week, as this could for instance be overtime at home in a week.
- For simplification purposes, only changes in WFH hours are considered to define a variable for a change in WFH and not changes in overall working or working at the workplace or elsewhere.
- Next, this research does not account for working from home on the day of filling in the travel diary. Many respondents fill in the diary for one or two weekend days, thus, this leads to different groups, not WFH at all, WFH but not on the survey days, WFH on the survey day. This would complicate the analyses. Otherwise, people who work from home but not on the survey day could be grouped with people who do not work from home. However, research found that people who work from home also adapt travel behaviour on days on which they do not work from home, such as weekends (Hamer et al., 1991).
- Finally, respondents in the MPN are asked to report their WFH hours *'in a recent week'*. Thus, the reported WFH hours per week are not necessarily the extent of WFH that is practiced during the week of filling in the travel diary.

4.2.2. 2021-2022: Decrease in WFH variable

This subsection lays out the operationalisation of a decrease in WFH variable, which is included in the transition model for 2021-2022. Studying the effect of a decrease in WFH is rather exploratory, the variable definition purely relies on descriptive data analyses.

From 2021-2022, the effect of a decrease in WFH on activity-travel patterns is studied as with the abolition of governmental measures a number of employees return to the workplace and, thus, they decrease WFH. However, a decrease in WFH is not necessarily due to a return to the workplace, it can also be due to a reduction in overall working hours. Thus, working hours are analysed at an aggregate and individual level. At an aggregate level, Table 4.3 shows that the average working hours remain approximately the same in both years.

Table 4.3: Average working hours 2021-2022

	N	Minimum	Maximum	Mean	Std. Deviation
Working hours per week 2021	726	3	70	33.9	8.671
Working hours per week 2022	726	1	70	33.72	8.974

An individual level analysis investigates the reductions in working hours for respondents for whom a decrease in WFH was found. Table 4.4 indicates the frequencies and extent of a decrease in working hours for respondents with a decrease in WFH hours in 2022. Given that respondents are asked about the working hours per week and not the weekly hours in their contract a certain variability between measurements appears naturally [5]. Hence, the range of a decrease or an increase up to 8 hours is assumed to be an acceptable variability due to overtime or similar. However, 9 respondents have a decrease in working hours of at least 10 hours, depicted behind the dotted line in Table 4.4. These 9 respondents are excluded from the sample for the second model, reducing the sample to N=717.

Table 4.4: Individual level analysis of a change in working hours 2021-2022

	Increase in working hours						No change	Decrease in working hours												Total
Change in working hours 2021-2022	8	6	4	3	2	1	0	-1	-2	-3	-4	-5	-6	-8	-10	-12	-18	-20	-37	
Frequency	2	1	4	1	2	2	59	4	3	1	4	2	1	3	3	3	1	1	1	98

Table 4.5 shows that creating two dummy variables, by defining a smaller and a larger decrease variable, as done for the increase variable, is not feasible. A decrease by +24 hours in WFH per week only occurs 8 times. This frequency is too low to explicitly model this effect. However, a decrease by 8-23 hours occurs 90 times, which equals 12 % of the sample. Thus, as a matter of simplification a decrease is defined as a decrease in WFH by at least 8 hours. Similar to the increase variable, an ordinal scale is chosen and defined as follows:

- **No decrease:** Representing no change in WFH, or a decrease of less than 8 hours per week, or an increase of any kind.
- **Decrease:** Representing a decrease by at least 8 hours per week.

This operationalisation comes with the limitation that large decreases are mixed up with smaller decreases which is accepted for now.

Another notable conclusion that can be drawn from Table 4.5, is that based on the studied sample no large decreases in WFH, corresponding to going back to work full-time occurred so far in May 2022.

Table 4.5: Changes in WFH hours per week between 2021 and 2022

	Change in WFH hours 2021-2022 (N=726)	Frequency	Percentage
Decrease	32+	4	1%
	24-31	4	1%
	16-23	18	2%
	8-15	72	10%
	1-7	81	11%
No change	0	429	59%
	1-7	73	10%
Increase	8-15	31	4%
	16-23	8	1%
	24-31	4	1%
	32+	2	0%

4.3. Other exogenous variables

The literature study in Section 2.3.3, revealed individual characteristics which have been controlled for by WFH and travel studies (Table A.1 in Appendix A). These variables influence the possibility and adoption to WFH and travel patterns. Hence, these variables should generally be controlled for. Pre- and during-COVID-19, WFH confounds with many other socio-economic and demographic variables,

[5] Respondents likely fill in the questionnaire with diverging precision. While some may just indicate the working hours in their contract, others may indicate the hours of overtime spent checking emails during the evening.

such as education or age (see Section 2.2.3). However, as the main objective of this research is to test the effect of a change in WFH on transitions in activity-travel patterns and not to test the effect of other factors on class membership, the latter are only included as inactive in the LCA. This allows holding the model parameters at a minimum, which is beneficial considering the rather small sample sizes. At the same time descriptive insights on these variables by adding them as inactive can still be gained. Nonetheless, three active covariates are added to the LCA, the rationales are given below. Active and inactive covariates can be included as nominal or numeric in Latent Gold.

4.3.1. Active covariates

Three active covariates are included in the **LCA**, the extent of working, the extent of WFH, and weekend days. The rational for including these variables as active covariates as well as the chosen scale are elaborated below. The weekend days are also included as predictors for initial class membership in the **LTA**. However, as reported weekdays remain the same in the MPN, this variable likely does not have a large influence.

Working hours per week

In Section 3.2.4, it is decided that a person is considered a worker as soon as she or he works 1 hour per week. To account for large differences in working extents this variable is added. Thus, working hours are included as an active covariate in the LCA to control for the fact that certain people work full-time while others do not, which likely affects the activity-travel patterns they belong to. The working hours per week are measured on a continuous scale in the MPN, which can be recoded to an ordinal scale. Models were run for a continuous and an ordinal scale. However, including this variable as numeric (continuous scale) leads to a better model fit.

WFH hours per week

WFH hours per week are added as a covariate to the LCA to identify whether WFH has an effect on activity-travel patterns. This allows to gain initial insights on the effect of WFH on activity-travel before studying the effect of a change in WFH on transitions in activity-travel patterns. It is expected that WFH significantly influences the activity-travel pattern a respondent belongs to. Similar to the previous variable, the WFH hours are available on a continuous scale. Also here the continuous scale is chosen instead of a transformed ordinal scale and the variable is included as numeric for the same reasons as above.

Reported weekend days

As indicated above, reported weekend days should be controlled for. This variable must be accounted for in the analyses as some respondents fill in the travel diary for one or two weekend days. Travel patterns on weekend days likely diverge from working days as less work trips are registered. Thus, similar to De Haas et al. (2018), a variable indicating the number of reported weekend days is included as a numeric covariate to account for class membership due to reporting travel on weekend days.

4.3.2. Inactive covariates

The operationalisation of inactive covariates is not thoroughly discussed but simply depicted in Table 4.6 below. For each variable, the original coding is indicated, recoding, and the chosen scale for running the **LCA**.[6] These individual characteristics are added as inactive to the LCA to additionally profile the identified activity-travel patterns, without adding parameters to the model.

[6] In Latent Gold nominal and ordinal variables are treated the same. Thus, if the table indicates an ordinal scale, a nominal scale was chosen in Latent Gold.

Table 4.6: Inactive covariates

	Variable	Coding/ Description	Scale
Personal variables	Age	Continuous variable	Numeric
	Gender	Male or female	Nominal
	Personal Income	Initially measured with 12 levels in the MPN. Recoded to 5 levels in accordance with levels used by Hamersma et al. (2021)	Ordinal
	Educational level	Initially measured with 8 levels in the MPN. Recoded to 3 levels in accordance with the definition by CBS.	Ordinal
	Sector	Initially measured with 20 levels in the MPN. Recoded to 8 levels based on sectors with the highest shares in the sample. The chosen levels align with the ones used by Hamersma et al. (2021)	Nominal
	Occupational status	3 levels included in the MPN: self-employed, employed non-governmental job, employed by the government	Nominal
Household characteristics	Family cycle	4 categories measured by the MPN	Nominal
Spatial variables	Level of urbanity	Initially measured with 5 levels in the MPN. Recoded to 3 levels in accordance with levels used by Hamersma et al. (2021) and most studies reviewed in Section 2 (urban; sub-urban; rural)	Ordinal
Mobility resources	Car license	Yes/no	Nominal
	Car availability	Count variable directly available in the MPN	Numeric
Others travel metrics	Business travel by all modes	Count variable, trip rates	Numeric
	Travel by other modes	Count variable, trip rates	Numeric
	Distances	Included as distances per purpose and mode and total average distance (in km) for three days. Trip distances are prone for outliers, thus, trips are cleaned by removing the following trips: 1) Trips > 450 km, as it is unrealistic to travel for 450 km in the Netherlands without stopping 2) Walking trips > 50 km	Numeric

Considering the variables presented in Table A.1 in Appendix A, the only variable which is not included is the job function. The job function is available for the 2021 data. However, for 2019 this information is only included in the MPN as an open-question. The job function could be imputed from 2021, but a considerable number of respondents indicated a different sector in 2021 compared to 2019. Hence, also the job functions is not imputed.

4.4. Operational model

Based on the explanations above and the conceptual model, the models of this research are operationalised.

In both the LCA and the LTA, indicators define activity-travel patterns. Activity-travel patterns describe unobserved travel behaviour by subgroups in the population. In the LCA, exogenous variables act as predictors for class membership or describe the classes, in case of inactive covariates. In the LTA, exogenous variables act as predictors for initial class membership and/or interact with the transitions.

Figure 4.3, shows the operational model of the LCA, used to identify the activity-travel patterns in the next chapter.

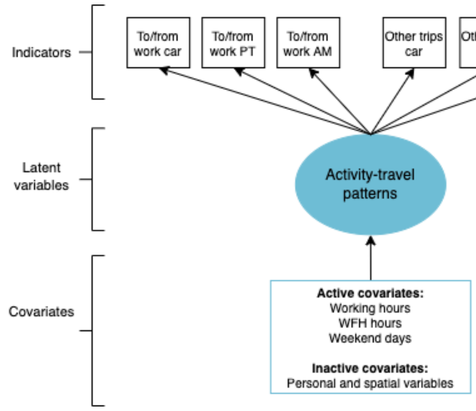


Figure 4.3: Operational model LCA

As explained in Section 4.2, two separate transition models are estimated due to technical limitations. Nonetheless, Figure 4.4 shows both operational models in one visualisation to emphasize the time structure, while Figure 4.5 and 4.6 show them separately. Thus, this research operationalises two models, with two time points each, to study three time points. By this, transitions between activity-travel patterns from pre-COVID-19 to during-measures and from during-measures to post-measures are studied. This model emphasizes the time structure of this research.

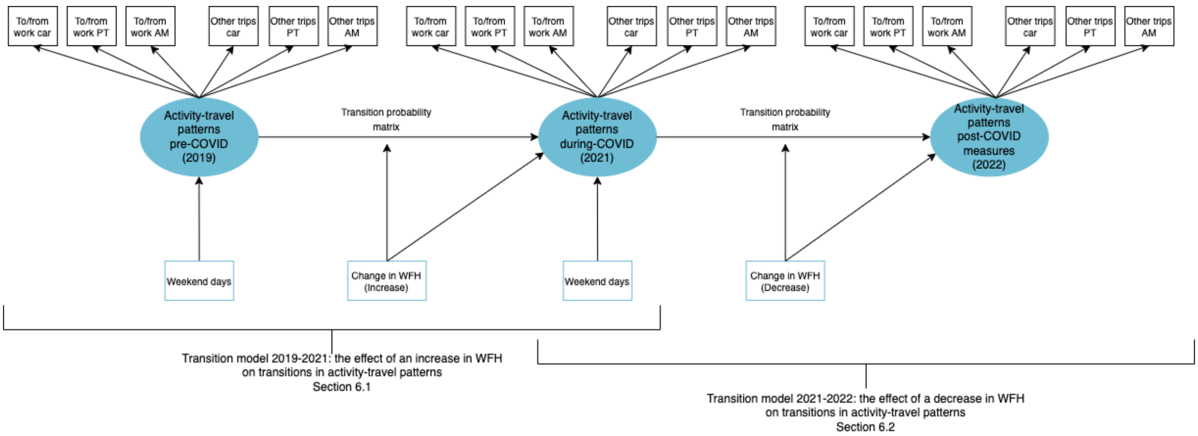


Figure 4.4: Model including all time points

Figure 4.5 depicts the operational model of the LTA for 2019-2021, which studies the effect of an increase in WFH. It must be noted that previous travel patterns inform future travel patterns.

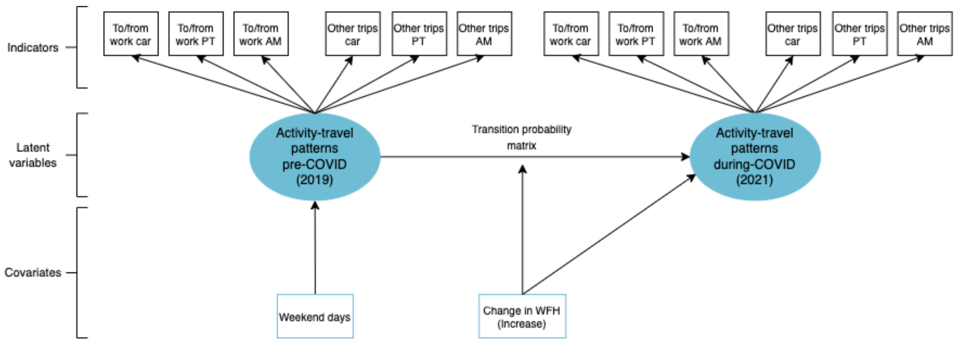


Figure 4.5: Operational model LTA 2019-2021

Finally, Figure 4.6 presents the operational model of the LTA for 2021-2022, which studies the effect of a decrease in WFH.

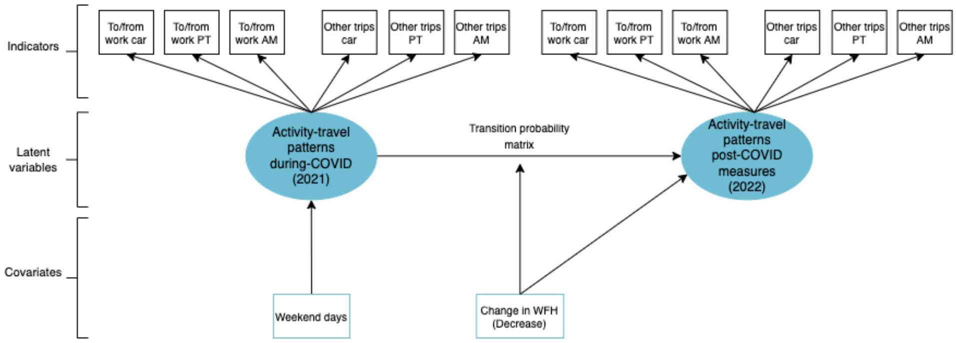


Figure 4.6: Operational model LTA 2021-2022

In both Figures 4.5 and 4.6, the change in WFH acts as a time-varying covariate. This variable is depicted by an arrow from a change in WFH to the transitions since these variables interact with transitions between classes. Thereby, activity-travel patterns in a subsequent time point are explained by a change in WFH, thus, also a direct arrow pointing to these patterns is included.

5
Identification of activity-travel patterns

Before studying transitions in activity-travel patterns, these patterns need to be identified using Latent Class Analysis. The analysis steps introduced in Chapter 3 are applied. First, the measurement model is studied to select the optimal class model indicating the number and nature of activity-travel patterns (step 1.1). Second, covariates are added to the selected class model, and the pattern description is presented (step 1.2).

The descriptions of activity-travel patterns for 2019-2021 are fully presented and discussed in Section 5.1. For 2021-2022, only notable qualitative differences compared to the 2019-2021 patterns are discussed in Section 5.2, while details are presented in the appendix. Finally, Section 5.3 discusses the findings and concludes this chapter.

5.1. Activity-travel patterns for 2019-2021

5.1.1. Model selection for 2019-2021

It is more defensible to motivate the optimal class model when separately testing the measurement model. Separately testing measurement models means estimating different class models, e.g. ranging from 1-10 classes, solely including the indicators but no covariates.

Model selection based on BVR, BIC and reduction of L^2

As motivated in Chapter 3, the BIC, the BVRs and the reduction of L^2 are used to select the number of activity-travel patterns. Next to these methods, the classes must be substantially meaningful. Thus, classes should be well interpretable and meaningful in size besides statistical criteria. Tiny cluster sizes, such as 2 %, are not relevant anymore and are prone to cause problems in the transition model in the subsequent step, as not many people belong to these classes.

Table 5.1 shows that the BIC is only of limited value as it decreases with each additional class. A lower BIC is preferred over a higher one. This would lead to selecting the 10-class model. While the class sizes remain sufficiently large for a 10-class model, such a model causes interpretability problems for the classes and leads to high interpretation effort. Besides this, a parsimonious model is preferred, and a 10-class model leads to a high number of parameters, especially in the subsequent LTA. Next, the BVRs and the reduction of L^2 are analysed for the model selection.

Table 5.1: Model fit information for 1-10 LCM for 2019-2021

	LL	BIC(LL)	Npar	L²	df	p-value	Reduction in L²	Additional Reduction in L²	Smallest class size	# significant BVRs (above 3.84)
1-Cluster	-36196	72441	6	28714	3542	5.5e-3860			100%	12
2-Cluster	-32400	64906	13	21122	3535	3.7e-2450	26%	26.4%	42%	14
3-Cluster	-30227	60617	20	16775	3528	2.0e-1685	42%	15.1%	31%	9
4-Cluster	-29178	58576	27	14678	3521	2.1e-1334	49%	7.3%	20%	9
5-Cluster	-28353	56983	34	13028	3514	3.6e-1069	55%	5.7%	11%	9
6-Cluster	-27730	55795	41	11781	3507	4.3e-877	59%	4.3%	10%	7
7-Cluster	-27279	54950	48	10880	3500	1.4e-743	62%	3.1%	7%	6
8-Cluster	-26896	54242	55	10114	3493	2.0e-634	65%	2.7%	7%	2
9-Cluster	-26641	53788	62	9604	3486	2.7e-564	67%	1.8%	7%	4
10-Cluster	-26422	53408	69	9166	3479	4.7e-506	68%	1.5%	6%	5

Generally, the absolute values of the BVRs start improving from a 4-class to a 5-class model, but they still remain significant. Concerning the local model fit, the 8-class model would be the most favourable, as only 2 BVRs remain significant, shown in Table 5.1. Also, with a higher number of classes, not all BVRs fall below 3.84, as already expected and explained in Chapter 3. In real-world scenarios, this assumption often needs to be relaxed as some indicators may have a correlation which they share, which is not due to the latent variable. Thus, the BVRs are considered here, but the local independence assumption is somewhat relaxed as one would otherwise end up with too many classes. For both the 6-class and 7-class models, most BVRs are below 3.84, but as expected, not all of them. Thus, as anticipated, both class models violate the local independence assumption.

Although the 8-class model suggests a better local fit, this model is not considered as it leads to a less parsimonious model with a high interpretation effort and lower class interpretability. Next, a model with less than 6-classes is not considered as the low mobility class only appears starting from a 6-class model. Given the WFH and the COVID context, a low mobility class is desired as some people are expected to transition to such a pattern after taking up or increasing WFH.

Table 5.1 indicates the additional reduction in L^2. No strict instructions exist on when the additional reduction suggests that it is still valuable to add an additional class. Existing empirical research uses values of an additional reduction in L^2 of less than 2 or 3 % (Kroesen, 2014; De Haas et al., 2018). Starting from a 6-class model, the additional reduction in L^2 falls below 5% and, hence, becomes very small with each additional class. After a 7-class model, the additional reduction falls below 3 %, suggesting that a 7-class model balances model fit and parsimony. Still, a more parsimonious model is generally preferred. Thus, the 6-and 7-class models are compared to decide whether the qualitative gain of a seventh class is worth choosing a less parsimonious model, which also implies higher interpretation effort.

Comparison of the 6 and 7 class model

Examining the profiles of the 6-class (Figure 5.2) and the 7-class (Figure 5.3) models, both models show high interpretability. The profiles depict the indicator means for the categories of the latent variable. All classes from the 6-class model are also present in the 7-class model with slight differences in absolute indicator values.

The new class that appears in the 7-class model mainly emerges from the 4th and the 6th class of the 6-class model and represents an additional active mode user class with many other trips (class 6, 7-class model). Hence, some respondents classified as active mode commuters (class 4) or multi-modal users (class 6) in the 6-class model form a second active mode user class in the 7-class model.

Although a 6-class model is more parsimonious and leads to less interpretation effort, the 7-class model is chosen for two reasons. First, COVID-19 literature shows an increase in popularity for trips by active modes, notably round trips (De Haas et al., 2020). Second, general WFH and travel literature shows that WFH may be associated with more trips by active modes. Hence, it is interesting to see whether people who increase WFH transition to this class. Against this background, the 7-class solution is chosen to profile activity-travel patterns.

Table 5.2: Profiles of the 6-class model 2019-2021

	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Cluster6
Cluster Size	22%	22%	18%	14%	14%	10%
Class label	Car users for many other trips	Car commuters	Car & AM users for many other trips	AM commuters	Low mobility	Multi-modal users
Indicators						
to/from work car	1.5	3.5	1.1	0.2	0.0	0.1
to/from work pt	0.1	0.0	0.0	0.0	0.0	1.6
to/from work am	0.1	0.0	0.5	3.5	0.0	0.2
other trips car	7.4	1.2	3.9	1.1	0.7	1.1
other trips pt	0.1	0.0	0.0	0.1	0.0	0.8
other trips am	0.9	0.8	6.8	2.5	0.4	3.6

Table 5.3: Profiles of the 7-class model 2019-2021

	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Cluster6	Cluster7
Cluster Size	21%	19%	19%	14%	11%	8%	7%
Class label	Car commuters	Car users for many other trips	Car & AM users for many other trips	Low mobility	AM commuters	AM users for many other trips	Multi-modal users
Indicators							
to/from work car	3.5	1.6	1.2	0.0	0.3	0.1	0.1
to/from work pt	0.0	0.0	0.0	0.0	0.0	0.1	2.1
to/from work am	0.0	0.1	0.4	0.0	3.7	1.4	0.2
other trips car	1.1	7.4	4.8	0.7	1.4	0.0	1.7
other trips pt	0.0	0.0	0.0	0.0	0.0	0.3	0.8
other trips am	0.8	0.6	6.0	0.4	1.6	6.9	2.8

5.1.2. 7 Activity-travel patterns for 2019-2021

Covariates are added to the 7-class model. For reasons elaborated in Chapter 3 and 4, most covariates are added as inactive except weekend days, WFH hours per week and working hours per week. Adding these active covariates only minimally changes the absolute indicator values of the class profiles, shown in Table 5.4.

According to the Wald-statistic, all indicators, active covariates and model for cluster intercepts are significant. Statistically significant active covariates show that working hours, WFH hours and reported weekend days are significant predictors for class membership. Significant model for cluster intercepts indicate that the coefficients are significantly different from 0. The null hypothesis is that the coefficients are equal to 0, meaning the class sizes are the same in the population. This null hypothesis is rejected. Hence, in the population, one would expect that the class sizes of the 7 clusters are indeed different from one another. All parameter estimates are depicted in Appendix C.

Table 5.4: Profiles of the 7-class model 2019-2021 incl. all covariates

	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Cluster6	Cluster7
Cluster Size	21%	19%	19%	15%	12%	7%	7%
Class label	Car commuters	Car users for many other trips	Car & AM users for many other trips	Low mobility	AM commuters	AM users for many other trips	Multi-modal users
Indicators							
to/from work car	3.6	1.6	1.1	0.0	0.3	0.2	0.1
to/from work pt	0.0	0.0	0.0	0.0	0.0	0.1	2.3
to/from work am	0.0	0.1	0.4	0.0	3.8	1.1	0.2
other trips car	1.2	7.4	4.8	0.8	1.3	0.0	1.6
other trips pt	0.0	0.1	0.1	0.0	0.0	0.3	0.8
other trips am	0.8	0.6	6.0	0.4	1.8	7.0	2.6
Active covariates							
Weekend days							
0	53%	31%	32%	35%	57%	44%	46%
1	28%	25%	26%	27%	25%	27%	28%
2	20%	44%	42%	37%	18%	28%	26%
Mean	0.67	1.13	1.10	1.02	0.61	0.84	0.80
WFH hours per week							
1-1	68%	54%	52%	48%	76%	41%	50%
2-3	4%	6%	5%	3%	3%	4%	4%
4-13	19%	21%	21%	14%	15%	19%	27%
14 - 54	9%	19%	22%	35%	6%	36%	19%
Mean	3.48	6.29	7.30	11.42	2.38	11.00	7.05
Working hours per week							
1-23	13%	21%	28%	17%	22%	26%	11%
24 - 30	16%	19%	23%	20%	22%	23%	20%
31 - 34	19%	15%	16%	18%	18%	20%	25%
35 - 37	38%	28%	21%	33%	29%	23%	33%
38 - 57	14%	16%	12%	12%	9%	8%	11%
Mean	36.52	34.99	32.64	35.28	33.93	32.13	35.99
Inactive covariates							
Age							
Mean	43.70	45.51	45.55	45.43	46.67	46.12	41.85
Gender							
Male	58%	47%	39%	55%	48%	38%	52%
Female	42%	53%	61%	45%	52%	62%	48%
Most applicable work situation							
Self-employed entrepreneur	4%	9%	7%	12%	6%	11%	4%
Employed non-governmental job	78%	73%	75%	73%	73%	64%	76%
Employed by the government	17%	19%	18%	16%	21%	25%	20%
Sector							
Healthcare	18%	19%	25%	16%	22%	19%	17%
(Retail) trade	11%	7%	6%	6%	10%	6%	6%
Automation and IT	7%	9%	7%	10%	4%	7%	9%
Education and science	10%	13%	12%	7%	17%	13%	10%
Industry and production	11%	7%	8%	8%	8%	4%	3%
Public administration, security and justice	5%	5%	7%	6%	4%	13%	11%
Financial services	4%	6%	7%	8%	4%	5%	11%
Others	33%	35%	29%	40%	30%	33%	33%
Education level							
Low	15%	13%	8%	20%	16%	11%	9%
Medium	40%	41%	38%	40%	42%	29%	31%
High	46%	46%	53%	40%	42%	60%	60%
Unknown	0%	0%	0%	0%	0%	0%	0%
Personal income							
<500-1500	8%	9%	9%	12%	9%	11%	7%
1501-2500	31%	32%	36%	31%	37%	35%	30%
2501-3500	34%	34%	34%	33%	30%	35%	40%
>3501	10%	11%	9%	10%	7%	9%	15%
Unknown	16%	12%	13%	15%	17%	10%	8%
Family Cycle							
Single	16%	22%	21%	16%	21%	33%	41%
Adult household	51%	41%	39%	55%	51%	39%	38%
Household with a youngest child with the age ≤ 12	23%	31%	34%	20%	17%	23%	19%
Household with a youngest child with the age of 13 up to 17	10%	6%	6%	8%	11%	5%	3%
Level of urbanization							
Urban, >1500 inhabitants/km^2	50%	49%	52%	57%	59%	70%	73%
Sub-urban, 1000-1500 inhabitants/km^2	17%	18%	18%	15%	16%	12%	14%
Rural, <1000 inhabitants/km^2	33%	33%	31%	28%	25%	18%	13%
Car license							
No	0%	0%	1%	6%	9%	14%	16%
Yes	100%	100%	99%	94%	91%	86%	84%
Car							
0	2%	1%	3%	13%	21%	35%	32%
1	95%	97%	93%	84%	78%	62%	62%
2	2%	2%	3%	1%	1%	0%	1%
4	0%	0%	0%	1%	1%	3%	5%
Mean	1.01	1.02	1.01	0.92	0.82	0.73	0.83

	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Cluster6	Cluster7
Cluster Size	21%	19%	19%	15%	12%	7%	7%
Class label	Car commuters	Car users for many other trips	Car & AM users for many other trips	Low mobility	AM commuters	AM users for many other trips	Multi-modal users
Inactive covariates (continued)							
Trips by other modes							
1-1	96%	97%	97%	88%	97%	96%	96%
2-14	4%	3%	3%	12%	3%	4%	4%
Mean (trip rates)	0.13	0.11	0.08	0.53	0.09	0.19	0.12
Business trips by all modes							
1-1	94%	94%	93%	95%	95%	91%	95%
2-8	6%	6%	7%	5%	5%	9%	5%
Mean (trip rates)	0.14	0.12	0.12	0.15	0.10	0.19	0.10
Distances							
to/from work car (in km)	95.68	36.84	26.14	0.18	4.40	3.90	2.53
to/from work PT (in km)	0.22	2.14	0.42	0.08	0.58	3.05	85.13
to/from work AM (in km)	0.19	0.47	2.04	0.05	18.09	5.32	1.08
to/from work others (in km)	1.69	1.65	0.52	8.97	0.75	2.44	0.77
non-work car (in km)	22.12	110.88	70.47	17.12	21.60	0.09	26.52
non-work PT (in km)	2.26	1.63	2.07	1.05	1.50	14.52	28.54
non-work AM (in km)	2.01	1.43	11.43	1.96	5.05	15.40	6.40
non-work others (in km)	0.82	1.91	0.67	3.53	0.65	0.51	0.57
Total distance (in km)	124.99	156.95	113.77	32.94	52.60	45.22	151.53

The classes are discussed based on indicator values, which are relevant for the profile labels and the active covariates. Other socio-demographics, operationalised as inactive covariates, are only discussed if strikingly different from other classes. Distances, operationalised as inactive covariates, are also discussed to assess the sustainability of car profiles. The indicator values are plotted for each class in Figure 5.1, making the labelling apparent.

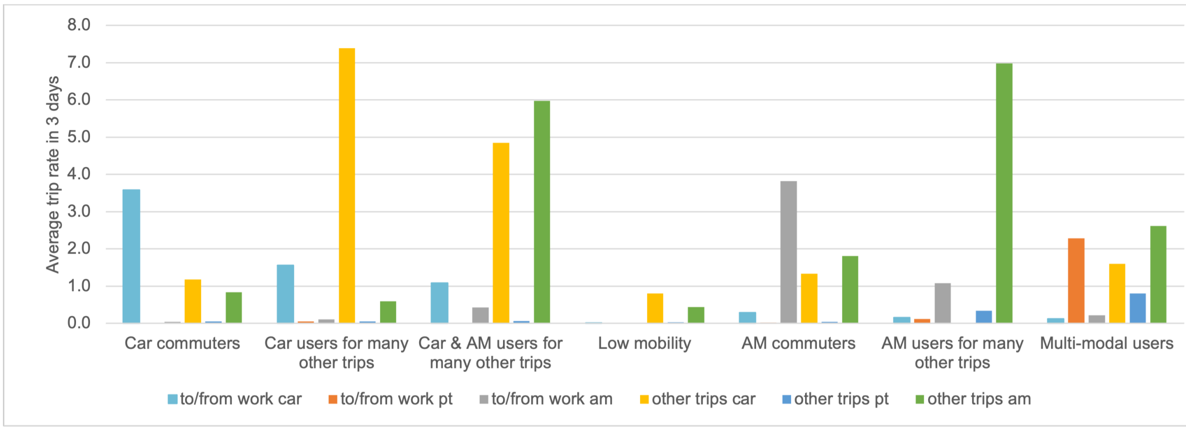


Figure 5.1: Overview of class profiles

1. Car commuters

The largest cluster in the sample is formed by strict car users with mostly work trips. 21 % of the respondents belong to this cluster. They take, on average, almost 3.6 work trips and about one other non-work trip by car in three days. Compared to other classes, this class includes a low mean value for reported weekend days, meaning not many people in this class filled in the diary on weekdays or only on one weekend day. This appears logical considering the high count of work trips in this class. Generally, most people work on weekdays. These car commuters present the second highest share for not WFH or only 1-3 hours with 72 %. At the same time, the mean working hours per week are the highest in this class, with 52 % working full-time, 35 or more hours per week.

2. Car users for many other trips

The second cluster presents again strict car users, forming a class size of 19 %. They have, on average, many trips for other non-work purposes by car, about 7.4 in three days, and only 1.6 for work. The high number of other trips and relatively lower work trips can partly be explained by the highest rate of two reported weekend days in this class. Still, compared to classes 1 and 5, this class also presents a high mean value for WFH. This class has the highest mean distance (in km) travelled in three days, 156.95 km, almost completely by car. Thus, this class is arguably the least sustainable class of all.

3. Car and AM users for many other trips
The third cluster represents car and active mode users who take many trips for other purposes. Similar to the previous class, this class shows a size of 19 %. On average, travellers in this class take 1.1 work trips by car in three days, 4.8 trips by car and 6 trips by active modes for other non-work purposes. These travellers show the second highest weekend rate, which again may explain the low work trip rate. However, also 51 % of these travellers work only up to 30 hours, which may also explain the low number of work trips and the high number of other non-work trips. Also, a considerable share, 22 %, work from home between 14 and 54 hours in this class.
This class also stands out because of some socio-demographics. Compared to other classes, larger disparities in the share of males and females are found, with 61 % females. This class also has the largest share of households with kids younger than 12. Thus, people with younger kids may take more non-work trips, likely due to pick-up and drop-off trips.

4. Low mobility
The fourth largest cluster are the low mobility travellers, representing 15 % of the sample. These travellers hardly take any trip at all in three days. They register about 0.8 trips by car and 0.4 by active modes for other non-work purposes. The weekend day rate in this cluster is again relatively high. Next, 63 % in this cluster work more than 30 hours. In terms of WFH, these travellers show the second highest share, 35 %, of WFH hours between 14-54 hours per week. This indicates that many people may adopt a low mobility activity-travel pattern when they work from home a lot. This underpins a strong *'cross-sectional'*[1] association of WFH and adopting low mobile behaviour. Although trips by other modes are not included as indicators, Table 5.4 shows that this class also has 0.5 trips by other modes. Analysing the distances, it appears that work trips by other modes account for the highest distances for work trips in this class. Thus, some people in this class may not really be low mobile for non-work trips. The distances also show that the low mobility class only presents a range, and individual people may not really be low mobile.

5. AM commuters
The fifth cluster, formed by approximately 12 %, represents active mode commuters. The number of work and other non-work trips is more or less balanced in this class. 3.8 work trips are strictly made by AM, while other trips are made by car (1.3) or active modes (1.8). The work trip rate by active modes is approximately the same as for work trips by car in the first cluster. Hence, it is unsurprising that the fifth cluster shows a similar average weekend day rate as class 1. Also, travellers in this cluster have the highest rate of not or hardly WFH with 76 %, who do so only up to 3 hours per week. In terms of socio-demographics, this cluster presents the highest mean age.

6. Active users for many other trips
The sixth cluster, with about 7 % of the sample, represents active mode users who take many other trips. This class emerges when going from a 6- to a 7-class model. On average, respondents in this cluster take 1.1 work trips and 7 trips for other purposes by AM. This profile shows the highest share, 36 %, of people who work from home a lot, meaning 14-54 hours per week. Similar to the low mobility class, this underpins a strong cross-sectional association between WFH and being part of class 6. This already confirms the argument for choosing the 7-class over the 6-class model. People who work from home are indeed prone to be part of this class. Nonetheless, this class is generally small in size. Thus, the absolute count of people showing this behaviour when working from home may not be incredibly high. Compared to the two other classes with many trips (2,3), the mean value for reported weekend days is relatively low. At the same time, this cluster counts the lowest mean working hours. Similarly to the third class, the share of males and females is rather out of balance in this cluster, counting more females than males. Also, this class has a significantly higher share of respondents residing in urban areas.

[1] One needs to remember that two time points are simultaneously considered in the LCA. Still, the strong association between WFH and activity-travel remains apparent.

7. Multi-modal users: PT commuters
The last cluster, formed by 7% of the sample, are the multi-modal users who commute by PT. It makes sense that this cluster is the smallest in size for two reasons. First, already before the pandemic, people commuted more by car and bicycle in the Netherlands than by PT (Buitelaar et al., 2021). Second, the profiles shown here contain pre-COVID and during-COVID data. During COVID, the share of PT users declined drastically (Hamersma et al., 2021). Next, this class presents the fourth highest mean rate of WFH hours per week. This aligns in general with what could be seen during the pandemic. Train travellers were more prone to start working from home. They are often highly educated people with jobs suitable to be conducted from home (Hamersma et al., 2020). In line with these expectations, this class contains the highest share of people with higher education, 60 %, and the highest shares in the higher income categories. At the same time, the class also contains the highest share of living alone. Similar to the previous class, the share of people residing in urban areas is very high. Concerning distances, this class has the second highest average distance travelled over three days, with 151.53 km, with the majority of kilometres travelled by PT for both to/from work and other non-work purposes. Still, they also have a significant distance by AM for non-work purposes.

5.1.3. Comparison of clusters

Comparing the seven clusters, three clusters (2,3,4) include noticeably more respondents who filled in the travel diary for two weekend days. Clusters 3 and 4 show that weekend days, high WFH levels, and not working full-time may lead to similar travel patterns. The other three clusters (1,5,7) are likely more prone to depict travel on weekdays. All three show the highest shares for reporting 0 weekend days on the survey days and the lowest shares of two weekend days. Finally, class 6 seems to depict weekday travel of people who work less or who work from home a lot.

Next, for each class, the mean distances travelled per purpose and mode in 3 days correlate with the number of trips, the indicators. The classes travelling by car (class 1, 2, 3) and multi-modal travellers (class 7) show the highest mean distances. Intuitively it makes sense that distances travelled by car and PT are higher than by AMs. Classes 4, 5, and 6, which are low mobile or travel by active modes, show considerably lower means for the distances travelled in 3 days, which makes sense intuitively. Thus, the classes, based on trip rates, can still indicate the sustainability of the activity-travel patterns.

Next, similar clusters appear based on trip rates per purpose but for other modes (car users vs. AM users). Class 1 (car commuters) and class 5 (AM commuters) show similar profiles based on the number of trips per purpose while showing different modes. The same applies to class 2 (car users for many other trips) and class 6 (AM users for many other trips).

5.2. Activity-travel patterns for 2021-2022

For the second transition period, the class-model selection is presented in Appendix D.

As introduced in Chapter 3 and Chapter 4, the transitions between 2021-2022 are based on a sub-sample of N=717 respondents. Hence, the activity-travel patterns are re-identified for these periods. Compared to the activity-travel patterns for 2019-2021, based on a sample of N=1774 wave pairs, slight qualitative changes appear in the class profiles. Tables 5.5 (1) and (2) depict the 7-class profiles for 2019-2021 and 2021-2022 [2], and the differences between both profiles are shortly discussed below.

[2] Tables 5.5 (1) and (2) depict the profiles based on a model estimations without covariates.

Table 5.5: Comparison of class profiles

(1)

2019-2021	**Cluster1**	**Cluster2**	**Cluster3**	**Cluster4**	**Cluster5**	**Cluster6**	**Cluster7**
Cluster Size	21%	19%	19%	14%	11%	8%	7%
Class label	Car commuters	Car users for many other trips	Car & AM users for many other trips	Low mobility	AM commuters	AM users for many other trips	Multi-modal users
Indicators							
To/from work car	3.5	1.6	1.2	0.0	0.3	0.1	0.1
To/from work PT	0.0	0.0	0.0	0.0	0.0	0.1	2.1
To/from work AM	0.0	0.1	0.4	0.0	3.7	1.4	0.2
Other trips car	1.1	7.4	4.8	0.7	1.4	0.0	1.7
Other trips PT	0.0	0.0	0.0	0.0	0.0	0.3	0.8
Other trips AM	0.8	0.6	6.0	0.4	1.6	6.9	2.8

(2)

2021-2022	**Cluster3**	**Cluster1**	**Cluster4**	**Cluster2**	**Cluster5**	**Cluster6**	**Cluster7**
Cluster Size	17%	19%	14%	18%	14%	10%	7%
Class label	Car commuters	Car users for many other trips	Car commuters & AM users for other trips	Low mobility	AM commuters	AM users for many other trips	Multi-modal users
Indicators							
To/from work car	3.4	1.0	2.7	0.0	0.2	0.0	0.2
To/from work PT	0.0	0.0	0.0	0.0	0.0	0.0	1.6
To/from work AM	0.0	0.3	0.1	0.0	3.5	1.4	0.2
Other trips car	1.5	7.4	1.3	0.9	0.8	1.3	0.6
Other trips PT	0.0	0.1	0.0	0.0	0.0	0.1	1.1
Other trips AM	0.1	2.8	4.3	0.5	1.4	8.2	2.8

Overall, six classes remain approximately the same for 2021-2022 compared to 2019-2021. The most notable difference between both profiles appears in class 3 (2019-2021) and class 4 (2021-2022), respectively. For comparability reasons, the first four classes in the profile summary for 2021-2022 are reordered, thus, classes are not ordered according to class sizes anymore.

1. **Car commuters:** This class remains approximately the same.
2. **Car users for many other trips:** In the 2021-2022 profile, this class counts 2.8 other trips by active modes (before 0.6) and a slightly lower count for car trips for work.
3. **Car commuters & AM users for other trips:** This class does not appear for 2019-2021. However, in 2019-2021 a class called **car and AM users for many other trips** exists. Both classes show high trip counts on the same indicators but the values change substantially, leading to different class labels. On average, 2.7 work trips by car are made by travellers in this class, and other non-work trips are mostly made by active modes (4.3 on average). Thus, from 2019-2021 to 2021-2022, this class changed the trip rates on the indicators, but the indicators showing trip rates remain unchanged.
4. **Low mobility:** This class remains approximately the same.
5. **AM commuters:** This class remains approximately the same, only the number of other trips by car slightly rises.
6. **AM users for many other trips:** In the 2021-2022 profile, this class additionally counts 1.3 other trips by car, which were 0 before.

7. **Multi-modal users:** In the 2021-2022 profile, this class slightly changes most absolute indicator values. However, the class label is still appropriate, and commute trips are still primarily done by PT.

Similar to the 2019-2021 analysis, a strong association between WFH a lot and being part of the low mobility class and being an AM user for many other trips appears for the 2021-2022 LCA. However, for 2021-2022 a similar association also appears for the multi-modal user class. A reason for this latter association may be that people who did not adopt working from home and commuted by PT pre-COVID still use other modes, while people who work from home a lot still use PT for their remaining commute trips. People who needed to commute during COVID-19 may have switched to individual modes and are still commuting by these. Alternatively, PT users may have increased their WFH hours during the pandemic due to increased WFH opportunities, which is not apparent in the 2019-2021 data due to the pre-COVID-19 time point.

5.3. Discussion and conclusion

This chapter reveals seven distinct activity-travel patterns based on pre-COVID and during-COVID or during-COVID and post-COVID data, respectively. Comparing patterns for both year pairs reveals that the identified patterns slightly change. Most classes remain the same, but one class changes the distribution of trips entirely, although keeping the same notable indicators. Hence, although 671 of the 717 respondents of the 2021-2022 sample were also present in 2019-2021, qualitatively identical patterns did not emerge. This points towards instability of identified patterns. Also, this limits the exact comparability between both transition models in the subsequent chapter. Differences in classes can be traced back to three reasons. First, a change in the sample size and composition can be the reason. Second, the evolving context and, hence, eventually evolving activity-travel patterns can be a reason. Due to COVID-19, which affected modes and activities, the patterns may indeed have slightly changed. Third, to the best of the author's knowledge, this research is the first attempt to simultaneously study activity-travel patterns based on modes and travel purposes. Existing studies defined patterns only on modes or only on activities (Kroesen, 2014; De Haas et al., 2018). Thus, the simultaneous use may make the patterns less stable. Re-estimating the models with only modes or purposes as indicators could bring further clarity.

Next, since the LCA is based on data from two years, the shares in WFH may seem lower than expected. However, based on the class compositions, one can expect that people who increased their WFH extent may have adopted the same patterns previously adopted by people who worked less or recorded their activity-travel behaviour for weekend days. Thus, reflecting on the use of the method and the available data, including respondents who filled in the travel diary on one or two weekend days, is beneficial. This likely allows finding patterns with low mobility on work trips also for the pre-COVID time point. This is necessary to assume measurement invariance to map the transitions between identical activity-travel patterns between two time points. If only workday travel data were used, the same travel patterns might not emerge in two subsequent time points due to considerable changes during the pandemic.

Next to simply identifying activity-travel patterns, active and inactive covariates are added as predictors for class membership or to describe the classes, respectively. A strong *'cross-sectional'* association between WFH hours per week and the low mobility class (class 4) and AM use for many other trips (class 6) results from the analysis. These associations appear in both the 2019-2021 and the 2021-2022 LCA and are thus judged to be relatively stable.

The identified activity-travel patterns present the starting point for the subsequent transition analysis.

6

Transitions between activity-travel patterns after a change in WFH

This chapter deploys the change in WFH variables defined in Chapter 4 to study the effect of an increase or a decrease in WFH on transitions in activity-travel patterns for 2019-2021 and 2021-2022. First, a transition model is estimated for 2019-2021 in Section 6.1, and the impact of an increase in WFH is studied. Second, a transition model is estimated for 2021-2022 in Section 6.2, and the impact of a decrease in WFH is studied.

Each time, average results between both years to reveal trends that may stem from COVID-19 are discussed first. These results are followed by a discussion on the impact of an increase or decrease in WFH on transitions in activity-travel patterns. Here, the impact of an increase in WFH is compared to average transitions and baseline values from 2019 and to transitions of people who did not have an increase in WFH. The effect of a decrease in WFH is discussed in less detail.

6.1. Transition model 2019-2021: the effect of an increase in WFH on transitions in activity-travel patterns

Given the small sample size and sparse data, the Latent Transition Model is estimated with only two active covariates. The change in WFH variable interacts with the transitions, and the reported weekend days are predictors for initial class membership. Working or working from home hours per week can not be added as predictors for initial class membership in Latent Gold, as they are time-varying covariates. Given the research aim, the working from home hours per week can alternatively be added to interact with transitions instead of the change in WFH variable. However, for reasons elaborated in Chapter 4 this option is not chosen. Adding both simultaneously is not recommended as both variables are highly correlated, and each additional variable leads to more model parameters. The profile output of the LTA model shows identical class profiles to the ones discussed and described in the previous section for 2019-2021.

6.1.1. General trends

Average transition matrix

The parameter estimates are presented in Table 6.1. Parameter estimates show the influence of a variable on class membership in the subsequent wave. A positive parameter implies an increased probability of transitioning to a certain class and the other way around with a negative parameter. All classes show negative and mostly significant parameters for the constants. Thus, classes positively affect themselves, meaning they tend to remain in their class.

Table 6.1: Parameters for the 2019-2021 transition model

		2021 class membership						
		1	2	3	4	5	6	7
2019 class membership		Car commuters	Car users for many other trips	Car & AM users for many other trips	Low mobility	AM commuters	AM users for many other trips	Multi-modal users
1 Car commuters	Constant	0	**-2.64 (0.00)**	**-1.95 (0.00)**	**-1.42 (0.00)**	**-2.44 (0.00)**	**-4.81 (0.00)**	**-4.46 (0.00)**
	Small increase (ref.=no increase)	0	***1.14 (0.09)***	0.2 (0.73)	***0.71 (0.07)***	-0.27 (0.75)	1.6 (0.29)	1.61 (0.21)
	Large increase (ref.=no increase)	0	**2.62 (0.00)**	1.33 (0.11)	**2.78 (0.00)**	0.63 (0.58)	**3.58 (0.03)**	**3.4 (0.01)**
2 Car users for many other trips	Constant	**-1.06 (0.00)**	0	**-1.55 (0.00)**	**-1.46 (0.00)**	**-1.9 (0.00)**	-4.72 (0.11)	**-4.42 (0.00)**
	Small increase (ref.=no increase)	-0.07 (0.89)	0	0.02 (0.98)	0.49 (0.27)	-1.89 (0.51)	2.2 (0.47)	1.59 (0.2)
	Large increase (ref.=no increase)	-2.01 (0.22)	0	0.69 (0.21)	0.63 (0.25)	-1.27 (0.25)	1.85 (0.56)	***2.23 (0.08)***
3 Car & AM users for many other trips	Constant	**-2.14 (0.00)**	**-1.73 (0.00)**	0	**-2.56 (0.00)**	**-2.03 (0.00)**	**-2.01 (0.00)**	**-3.01 (0.00)**
	Small increase (ref.=no increase)	0.87 (0.12)	0.46 (0.37)	0	0.01 (0.99)	-0.19 (0.79)	0.34 (0.59)	-5.36 (0.66)
	Large increase (ref.=no increase)	-5.59 (0.65)	0.5 (0.48)	0	***1.34 (0.08)***	-4.56 (0.71)	**1.63 (0.01)**	-4.49 (0.71)
4 Low mobility	Constant	**-1.38 (0.00)**	**-2.88 (0.00)**	**-3 (0.00)**	0	**-1.85 (0.00)**	**-2.29 (0.00)**	**-4.06 (0.00)**
	Small increase (ref.=no increase)	0.13 (0.85)	**1.93 (0.02)**	-4 (0.74)	0	-1.09 (0.34)	-1.5 (0.58)	-3.69 (0.76)
	Large increase (ref.=no increase)	-6.39 (0.6)	***1.62 (0.07)***	-4.72 (0.7)	0	-1.46 (0.43)	0.44 (0.66)	-3.67 (0.76)
5 AM commuters	Constant	**-2.37 (0.00)**	**-2.02 (0.00)**	**-4.09 (0.00)**	**-1.75 (0.00)**	0	**-2.4 (0.00)**	**-4.47 (0.00)**
	Small increase (ref.=no increase)	***1.36 (0.08)***	**1.44 (0.03)**	**3.38 (0.02)**	**1.29 (0.05)**	0	***1.5 (0.1)***	-2.17 (0.86)
	Large increase (ref.=no increase)	-2.56 (0.83)	-2.77 (0.82)	**5.63 (0.00)**	**3.9 (0.00)**	0	-1.18 (0.92)	**5.15 (0.00)**
6 AM users for many other trips	Constant	-5.65 (0.5)	-4.66 (0.4)	**-0.96 (0.00)**	**-1.81 (0.00)**	**-0.65 (0.05)**	0	-8.08 (0.5)
	Small increase (ref.=no increase)	-2.04 (0.89)	2.47 (0.66)	-4.22 (0.7)	0.14 (0.89)	-6.88 (0.57)	0	5.66 (0.64)
	Large increase (ref.=no increase)	-0.82 (0.96)	-2.83 (0.83)	-0.47 (0.56)	-4.84 (0.69)	-1.07 (0.22)	0	6.15 (0.61)
7 Multi-modal users	Constant	**-1.23 (0.00)**	**-2.07 (0.00)**	**-1.73 (0.00)**	**-1.68 (0.00)**	**-1.42 (0.00)**	**-1.71 (0.01)**	0
	Small increase (ref.=no increase)	0.1 (0.9)	0.84 (0.36)	0.7 (0.39)	**1.68 (0.02)**	-5.47 (0.65)	1.27 (0.13)	0
	Large increase (ref.=no increase)	0.4 (0.59)	-3.27 (0.77)	0.95 (0.29)	**1.74 (0.02)**	-5.5 (0.65)	0.69 (0.46)	0

P-values depicted in parentheses
Parameters p<0.05 are bold
Parameters p<0.1 are bold and italic

Overall, 59 significant transition parameters are found for this model, depicted in Table 6.1. For the increase in WFH variable, 21 estimates are significant at 0.05 or 0.1 significance levels, respectively. Hence, certain transition probabilities differ significantly after a small or a large increase in WFH and effects differ across the different classes. An overview is given below, and the discussion of underlying reasons follows afterwards.

- **Small increase in WFH:**
  Four out of seven classes show an increased probability to transition. Classes 2, 3 and 6 are not significantly affected.
  - Class 1 has an increased probability of transitioning to class 2 and class 4.
  - Class 4 has an increased probability of transitioning to class 2.
  - Class 5 has an increased probability of transitioning to all classes except class 7 (the multi-modal class).
  - Class 7 has an increased probability of transitioning to class 4.
- **Large increase in WFH:**
  In all classes, except class 6, a large increase in WFH increases the probability to transition significantly.
  - Class 1 has an increased probability of transitioning to classes 2, 4, 6 and surprisingly, even class 7.
  - Class 2 has an increased probability of transitioning to class 7, again surprising.
  - Class 3 has an increased probability of transitioning to classes 4 and 6.
  - Class 4 has an increased probability of transitioning to class 2.
  - Class 5 has an increased probability of transitioning to classes 3, 4 and 7.
  - Class 7 has an increased probability of transitioning to class 4.

Surprisingly, the low mobility class (class 4) shows increased probabilities of transitioning to class 2 for both WFH increase levels. Transitions from the low mobility class to classes with more trips are counter-intuitive and unexpected after an increase in WFH. Not including business travel and other modes could be why respondents are classified as low mobile in 2019. However, additional analyses show that this is likely not the case (see Table 5.4, Chapter 5). Another reason could be that these people only travel for non-personal reasons or abroad in 2019. The most likely explanation could be that the respondents showed a form of soft refusal. Thus, they under-reported their trips in 2019, indicating no travel although they travelled (De Haas et al., 2017). Due to the use of self-reported panel data, this is likely the case. De Haas et al. (2017) identified distinct types of immobility in the MPN. Soft refusal may cause certain unexpected transitions from the low mobility class to classes with higher mobility after an increase. After increasing WFH, respondents may have found time to fill in the travel diary in 2021 properly. De Haas et al. (2018) gave a similar explanation for increases in low mobility after a job change. People have less free time and, consequently, start showing soft refusal. A remaining explanation for counter-intuitive transitions could be that respondents travelled differently during the days of filling in the travel diary in one year due to personal reasons, e.g. being sick.

Surprisingly, increased probabilities appear to transition towards class 7, the multi-modal users, after a large increase in WFH. This could mean that when people increase WFH, they become more likely to use PT for commute travel on the 1-2 days they go to the workplace. So, once people save time on commute travel on several days, they may have a higher propensity to use PT. Another explanation could be that being used to working from home, they may use the commute time in PT to telework.

Next, Table 6.2 depicts the average transition matrix, including the average transition probabilities. The matrix shows that the probability of keeping the same activity-travel pattern in 2021 ranges between 50-61 % except for the multi-modal users (class 7). The probability of staying a multi-modal user in 2021 is only 40 %. As explained in Section 5.1.2, the multi-modal user group commutes by PT. The low probability of remaining in the multi-modal user class depicts a COVID-19 impact. The use of shared modes was generally discouraged by the government. Thus, PT-users were more prone to change to another modality but also to take up WFH as they often have suitable jobs and, hence, change their activity-travel patterns (see Section 2.2.3). Still, for all classes, the probabilities on the diagonal are the highest, shown in bold in Table 6.2. This means that respondents are more likely to remain in the initial class than to transition to another activity-travel pattern.

Table 6.2: Average transition matrix 2019-2021

	2019	2021 1 Car commuters	2 Car users for many other trips	3 Car & AM users for many other trips	4 Low mobility	5 AM commuters	6 AM users for many other trips	7 Multi-modal users
Average Transition Matrix	1	**0.54**	0.07	0.09	0.22	0.05	0.01	0.02
	2	0.15	**0.50**	0.12	0.14	0.06	0.01	0.02
	3	0.07	0.12	**0.56**	0.06	0.06	0.11	0.02
	4	0.13	0.09	0.02	**0.61**	0.07	0.06	0.01
	5	0.06	0.09	0.08	0.18	**0.50**	0.06	0.02
	6	0.00	0.02	0.14	0.08	0.18	**0.55**	0.03
	7	0.12	0.05	0.09	0.16	0.07	0.11	**0.40**

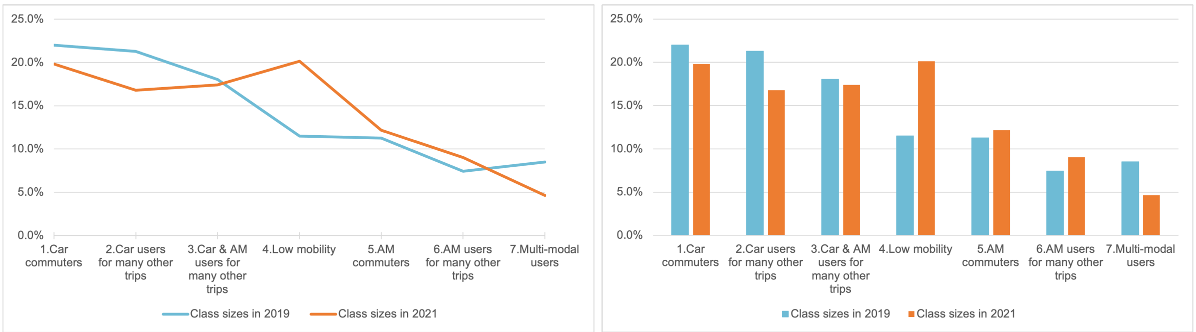
According to the average transition matrix, four classes (1, 2, 5, 7) show relatively high probabilities of transitioning to the low mobility class (class 4) in 2021. At the same time, the low mobility class shows the highest probability of remaining in their class in the second year. Again, dropping mobility levels are likely a COVID impact. However, considerable transition probabilities from classes with many commute trips (class 1,5,7) to the low mobility class point towards adopting or increasing WFH in the sample.

Since the probabilities in the transition matrix point towards considerable transitions in activity-travel patterns, the class sizes in both years are analysed and discussed in the next paragraph.

Class sizes

Figure 6.1 (1) depicts the development in class sizes between both years. Comparing the class sizes for 2019 and 2021, the share of travellers with high car usage decreases (class 1 and 2) or remains the same (class 3). A remarkable increase of the low mobility class (class 4) appears, apparent in

Figure 6.1 (2). Next, a slight increase in active mode commuters (class 5) and active mode users with many other trips (class 6) also appears in 2021. As expected, the share of the multi-modal users (class 7), including PT commuters, decreases in 2021. This likely has two reasons. First, the multi-modal users have a low probability of remaining in their class due to the recommendation to avoid PT and their generally higher propensity to adopt WFH during the pandemic (Section 2.1.2 and Section 2.2.3). Second, other classes have a very low probability of transitioning to this class, likely also due to the COVID context. However, existing literature on transitions in mobility patterns also found similar results. The probability of transitioning from another modality pattern to a PT class is very low (De Haas et al., 2018).



(1) (2)

Figure 6.1: Development of class sizes 2019-2021

Having presented general trends in transitions, the following section analyses and discusses transitions between activity-travel patterns after an increase or no increase in WFH.

6.1.2. Effect of an increase in WFH on transition probabilities

The parameter estimates allow computing transition matrices for the occurrence of a specific change in WFH. The share of people with an increase in WFH makes up 33.8 % of the whole sample. This likely explains why the no increase matrix, Table 6.3 (2), is remarkably different from the average transition matrix (Table 6.3 (1)). Against this background, the following compares matrices after a small or large increase in WFH to the matrix when no increase occurs. Thereby, this research can conclude on the effect of an increase in WFH on transitions in activity-travel patterns under the limitation of using COVID data. General WFH and travel literature compares travel patterns of people who work from home to those of people who do not. This research compares transition probabilities after an increase in WFH to probabilities if no increase occurs to investigate the effect of a change in WFH.

Latent Gold uses significant and non-significant model parameters to compute the matrices discussed in this section. These matrices are depicted in Table 6.3. Probabilities in bold highlight the probability of remaining in the same class in the second year. Next, the colour shades in Table 6.3 highlight low probabilities to stay or transition in/ to a class in blue, while high probabilities are highlighted in red colour shades.

Table 6.3: Transition matrix for the occurrence of no increase or an increase

		2019	2021: 1 Car commuters	2 Car users for many other trips	3 Car & AM users for many other trips	4 Low mobility	5 AM commuters	6 AM users for many other trips	7 Multi-modal users
(1)	Average Transition Matrix	1	**0.54**	0.07	0.09	0.22	0.05	0.01	0.02
		2	0.15	**0.50**	0.12	0.14	0.06	0.01	0.02
		3	0.07	0.12	**0.56**	0.06	0.06	0.11	0.02
		4	0.13	0.09	0.02	**0.61**	0.07	0.06	0.01
		5	0.06	0.09	0.08	0.18	**0.50**	0.06	0.02
		6	0.00	0.02	0.14	0.08	0.18	**0.55**	0.03
		7	0.12	0.05	0.09	0.16	0.07	0.11	**0.40**
(2)	No increase in WFH	1	**0.64**	0.05	0.09	0.15	0.06	0.01	0.01
		2	0.18	**0.51**	0.11	0.12	0.08	0.00	0.01
		3	0.07	0.11	**0.59**	0.05	0.08	0.08	0.03
		4	0.15	0.03	0.03	**0.61**	0.10	0.06	0.01
		5	0.06	0.09	0.01	0.11	**0.66**	0.06	0.01
		6	0.00	0.00	0.18	0.08	0.25	**0.48**	0.00
		7	0.13	0.06	0.08	0.08	0.11	0.08	**0.45**
(3)	Small increase in WFH	1	**0.49**	0.11	0.08	0.24	0.03	0.02	0.03
		2	0.16	**0.48**	0.10	0.18	0.01	0.04	0.03
		3	0.14	0.15	**0.52**	0.04	0.06	0.10	0.00
		4	0.16	0.22	0.00	**0.57**	0.03	0.01	0.00
		5	0.11	0.16	0.14	0.18	**0.29**	0.12	0.00
		6	0.00	0.08	0.00	0.14	0.00	**0.72**	0.06
		7	0.09	0.08	0.10	0.28	0.00	0.18	**0.28**
(4)	Large increase in WFH	1	**0.14**	0.14	0.07	0.54	0.02	0.04	0.05
		2	0.02	**0.47**	0.20	0.21	0.02	0.03	0.05
		3	0.00	0.13	**0.44**	0.13	0.00	0.30	0.00
		4	0.00	0.19	0.00	**0.68**	0.02	0.11	0.00
		5	0.00	0.00	0.29	0.53	**0.06**	0.00	0.12
		6	0.00	0.00	0.15	0.00	0.11	**0.64**	0.09
		7	0.13	0.00	0.14	0.32	0.00	0.11	**0.30**

Probability to remain in the same class in bold

Transition/ stayer probabilities

Low **High**

No increase in WFH

The diagonal in the matrix in Table 6.3 (2) shows that if no increase in WFH occurs, the probability of remaining in the same class is the highest for each class, similar to the average transition matrix, Table 6.3 (1). However, the matrix deviates remarkably from the average transition matrix. This is likely due to the high frequency of increases in WFH in the sample (33.8 %) affecting the average transition matrix, pointing to an effect of WFH on activity-travel patterns.

Compared to the average transition matrix, the probabilities of remaining in the same class in the subsequent year are higher for each class, except for active mode users with many other trips (class 6). This points towards more stability in activity-travel patterns when no increase in WFH occurs. Particularly classes with a high number of work trips have a higher probability of remaining in their class if no increase occurs: Class 1 shows an increase by 10 %, class 5 an increase by 16 % and class 7 an increase by 5 % of remaining in their classes compared to the average transition matrix. These findings are in line with expectations. People who do not increase their WFH extent have less reason to transition between classes because they still need to commute to work.

Due to the recommendation to avoid PT during COVID-19, it is not surprising that multi-modal users have the lowest probability of remaining in their class.

Otherwise, with slight increases and decreases, the off-diagonal probabilities are not much different from the ones in the average transition matrix. The highest transition probability is seen for active mode users with many trips (class 6). They have a 25 % probability of becoming AM commuters (class 5) in 2021. Next, the first five classes have a lower probability of transitioning to the low mobility class compared to the average transition matrix. Hence, high transition probabilities towards the low mobility class in the average transition matrix are likely explained by respondents who had an increase in WFH. This is in line with the substantial amount of significant positive parameters to switch to the low mobility class (class 4) after an increase in WFH, presented in Section 6.1.1.

Small increase in WFH
After a small increase in WFH, the probability of remaining in the same class is lower for all classes than when no increase in WFH occurs, except for class 6. Thus, after a small increase in WFH, people are more likely to transition. Still, for all classes except the multi-modal users (class 7), the probability of remaining in the same class is the highest. For the multi-modal users, the probability of transitioning to the low mobility class (class 4) is at 28 %, equalling the probability of remaining in their initial class.

Two transition trends appear when analysing the transition matrix in Table 6.3 (3):

1. **Increased transition probabilities towards the low mobility class (class 4) and AM users with many other trips class (class 6):** Generally, all classes show an increased probability of transitioning to the low mobility class, except class 3. Notably, the classes with many work trips (1,5,7) show the highest probabilities of transitioning to the low mobility class. This finding corresponds with the 'cross-sectional' findings in Section 5.1.2. Respondents in classes 4 and 6 showed high shares of WFH.

   Multi-modal users (class 7) have the highest probability of switching to the low mobility class and becoming AM users with many other trips (class 6). They do not transition to car profiles, which may show general attitudes towards modes of this group. At the same time, the complete profile of the 7-class LCA (Table 5.4 in Section 5.1.2) shows that 32 % of class 7 does not have a car. Thus, transitioning towards car profiles is unlikely. Besides this, many (> 70%) live in urban areas. Hence, distances to amenities are lower, which may explain the transition to AM profiles. The only other class that shows an increased probability (of 12 %) of transitioning to class 6 are AM commuters (class 5). Also, in this class, about a fifth does not have a car.

2. **Increased transition probabilities towards car profiles (class 1 and 2):** First, the first five classes show increased probabilities of transitioning to class 1. For class 2, this can be explained by doing fewer trips and less trip chaining. Going straight to work and home again results in more work trips and a reduction in other trips. For class 3, a similar explanation holds. Unexpectedly, the low mobility class also has a high probability of transitioning to class 1. Second, all classes show higher probabilities of transitioning to class 2 and becoming a car user with many other trips compared to the no increase matrix. This could point towards a generation of travel when working from home. Thus, reducing commutes can lead to an increase in other trips by car. These findings support a complementarity view. Surprisingly, the low mobility class has a probability of 22% to transition to class 2. Surprising results related to the low mobility class can again be explained by the reasons given in Section 6.1.1 above.

   AM commuters (class 5) have increased probabilities of switching to car classes (class 1,2,3). Thus, some people from class 5 in 2019 transition towards less sustainable profiles while others opt for the low mobility class or become AM users with many other trips. Generally, class 5, which only has a probability of 29 % of remaining in their class, shows a more or less even distribution of probabilities to all other classes except the multi-modal class.

The explanations above show how diverse and partly unexpected results are when studying the effect of a small increase in WFH. The transitions are certainly mixed-up with COVID-19 impacts, but differences to the cases without an increase in WFH are still notable. Slightly higher transitions towards car profiles (class 1 and 2) are worrying.

Large increase in WFH
After a large increase in WFH, all classes, except classes 4 and 6, have a lower probability of remaining in the same class compared to the no increase matrix. Classes 4 and 6 count no or hardly any com-

mute trips. Thus, it seems intuitive that these classes show a high probability of remaining in their class.

As this section studies the effect of a large increase in WFH, the three classes with many commute trips (classes 1,5 and 7) are particularly interesting:

- Travellers in classes 1, 5 and 7 in 2019 have a higher probability of transitioning to the low mobility class than remaining in their initial classes. This is depicted by red coloured cells in the low mobility column in Table 6.3 (4). The probabilities of remaining in class 1 and class 5 practically vanish, only remaining at 14 % and 6 %, respectively. Hence, a large increase in WFH hours drastically changes people's otherwise inert travel behaviour. The high transition probabilities to the low mobility class of 54, 53 and 32% show that many people substitute their commute trips by working from home without making additional non-work trips. They seemingly even decrease their trips for other purposes. This points towards a similar substitution effect as found by early WFH and travel studies (Mokhtarian, 1991b).
- Still, class 5 also has a high probability of 29 % of transitioning to class 3 - car and AM users with many other trips. This points towards making more car trips than before. Thus, a less sustainable profile is adopted. Since these people commuted by active modes before, they likely have not gained much time from the saved commute. Hence, they may use the increased flexibility of scheduling their day when working from home to make these trips and not so much the saved time. Other reasons may be that a partner works from home as well and a car becomes available. Unexpectedly, class 5 also has a higher probability of becoming multi-modal users. Possible explanations for transitions towards the multi-modal class have already been elaborated on above in Section 6.1.1.

After a large increase in WFH, transitions towards car profiles, classes 1 and 2, are lower than after a small increase in WFH. People primarily transition to the low mobility class, except travellers from classes 3 and 6. Class 3 is more prone to transition to class 6, with a probability of 30 %. Generally, classes 3 and 6 change to more active profiles. Thus, independent of the level of an increase in WFH, certain people may inherently have more active lifestyles. Thus, the effect of WFH on transitions in activity-travel patterns depends on initial class membership. Nonetheless, transitions towards classes 4 and 6 correspond well with the 'cross-sectional' findings, which showed that people who work from home a lot are in classes 4 or 6. Similarly to a small increase in WFH, the low mobility class again shows a high probability of transitioning to class 2, car users with many other trips. Possible reasons are given in Section 6.1.1.

Although the transition probabilities depict interesting movement between classes, the effect of an increase in WFH on class sizes can bring more insight into the potential transportation benefits of WFH. Adjustments in class sizes depict an aggregated view of the effects of WFH.

6.1.3. Effect of an increase in WFH on class sizes

Figure 6.2 shows the effect of an increase or no increase in WFH on class sizes for the subsequent year. The blue bar depicts class sizes in 2019 as a baseline.

The car and AM users with many other trips (class 3) is the only class which keeps roughly the same shares after each increase or no increase in WFH.

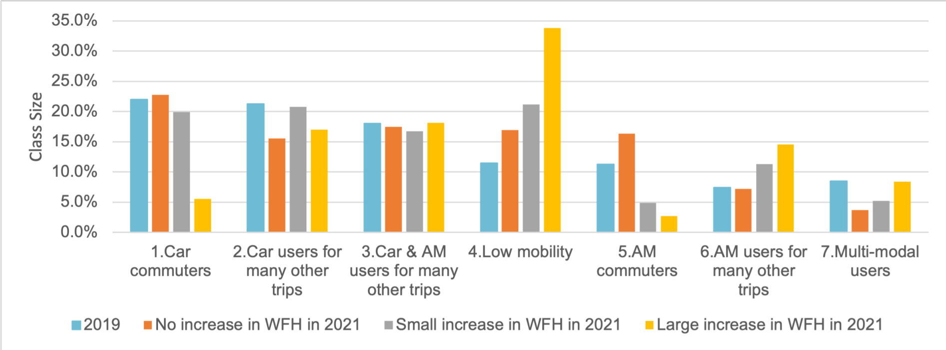


Figure 6.2: Share of activity-travel patterns after occurrence of (no) increase

If **no increase in WFH** occurs, the class sizes remain fairly similar to 2019 for classes 1, 3 and 6. The shares of the car users with many other trips (class 2) and the multi-modal class (class 7) decrease, which is likely a COVID-19 consequence of reduced activity and the recommendation to avoid PT. In turn, the share of AM commuters (class 5) increases. This comes from multi-modal and AM users with many other trips switching to this class. Next, after no increase in WFH, the share of the low mobility class increases, again showing a COVID-19 consequence of generally decreased activities. People may have been absent from work due to COVID-19, they may have filled in the diary on weekend days, or they may not work on the reported diary days while generally decreasing their activities during the pandemic. Nonetheless, some people may also have under-reported trips.

In Section 5.1.1, a 7-class model is selected because an AM user with many other trips class (class 6) emerges. This class is expected to be important after an increase in WFH. While the share of this class remains approximately the same if no increase occurs, it rises after an increase in WFH. This confirms the choice of including this class. Thus, the expectation that people who work from home make more trips by active modes for other purposes than people who do not is validated. This is in line with the findings of existing studies, which point towards a positive association between active travel and WFH (Elldér, 2020; Chakrabarti, 2018).

As expected after analysing the transition matrix after a **small increase in WFH**, car user classes (class 1 and 2) remain rather high in shares. The share of car users with many other trips is even higher than for 2019 or the no increase case. The shares of AM commuters (class 5) and multi-modal users (class 7) are rather low. In turn, the low mobility class (class 4) and the active mode users with many other trips (class 6) increased in shares compared to 2019, and the no increase in WFH case.

The most remarkable effects on class sizes appear after a **large increase in WFH**. In this case, car commuter and active mode commuter shares decrease drastically. Since these patterns count the highest number of commute trips, this finding is intuitive. The decreases in these class sizes primarily benefit the low mobility class and the active mode users with many other trips. Thus, more sustainable classes increase in shares after a large increase in WFH. Given the COVID-19 context, the share of multi-modal users is not expected to remain stable in 2021. Ozbilen et al. (2021) found that WFH is related to less time spent on PT, while de Abreu e Silva and Melo (2018) found that WFH is related to more miles by PT. This research does not study duration or distances. However, the results show that people who increased their working from home extent are generally more prone to continue using PT for their remaining commutes than people who did not increase WFH. However, Figure 6.2 shows that after a large increase in WFH the share of multi-modal users commuting by PT is similar to initial cluster shares in 2019. Hence, people who increased WFH may still make remaining commutes by PT. This result is probably linked to a finding by Hamersma et al. (2020) that people who commuted by train before COVID-19 were more likely to increase WFH during the pandemic.

High shares in low mobility point towards substitution in commutes and other trips. However, this substitution is likely amplified by the general COVID-19 travel-activity reductions.

6.1.4. Discussion and conclusion

Having analysed the impact of an increase in WFH on transitions between activity-travel patterns and on class sizes, main conclusions can be drawn.

Without an increase in WFH, people are more inert. They are more likely to remain in their activity-travel patterns in 2021 than people who increased their WFH hours. This holds especially for classes with many work trips (classes 1,5,7).

A small increase in WFH has very different effects on transitions. Two main trends are identified: 1) transitions towards low mobility or active profiles and 2) transitions towards car profiles. Concerning the latter, even people who were sustainable mode users in 2019, e.g. class 5, become likely to transition towards car profiles. Generally, transitions towards car profiles (classes 1 and 2) are worrying against the background of stimulating WFH. Analysing the impact of a small increase in WFH on class sizes confirms this concern. Overall the share of car travellers remains relatively high after a small increase in WFH. Thus, an increase by 1-3 days WFH may not lead to more sustainable or accessible activity-travel patterns defined in trip rates per purpose and mode. After a small increase, the share of car users with many other trips is even the highest in 2021. This finding is worrying as additional analyses find that this class also shows the furthest average distance travelled in three days[1]. It may be expected that once people start to decrease their working days at home to only 1-3 days per week, car profiles may exceed the pre-COVID shares. Nonetheless, the most evident trend is that most classes are more likely to transition towards the low mobility class, especially classes with many work trips (1,5,7).

After a large increase in WFH, higher probabilities of transitioning than remaining in the initial class appear for classes with many work trips (1, 5, 7). They appear not inert at all anymore. The low mobility class shows large increases, primarily due to transitions from classes 1, 5 and 7. Hence, overall substitution is apparent as the low mobility class becomes very popular for people from a class with many commute trips. Generally, after a large increase in WFH, two sustainable classes rise in shares (classes 4 and 6). Thus, a large increase in WFH may lead to more sustainable activity-travel patterns. Furthermore, high shares of the low mobility class show that a large increase in WFH favours accessibility of the mobility system.

Across all three transition matrices, car and active mode users with many other trips (class 3) and active mode users with many other trips (class 6) do not behave like other classes. They have comparatively low probabilities of becoming part of the low mobility class, which may point to underlying characteristics of these classes. They may generally have a higher trip demand due to more active lifestyles. These lifestyles may be linked to socio-demographics. These two classes stand out given their imbalances in gender shares, with significantly more females, the largest share of households with kids younger than 12 years (class 3) and a high share of people residing in urban areas (class 6). Thus, the results show that transitions between activity-travel patterns depend on initial class membership.

Nonetheless, transitions towards the low mobility class represent a reduction in travel for all classes. For both types of increases, this is the most pronounced effect.

6.2. Transition model 2021-2022: the effect of a decrease in WFH on transitions in activity-travel patterns

The second transition model is estimated with a considerably smaller sample of N=717 wave pairs. A decrease in WFH variable is included as a time-varying covariate to interact with the transitions. Besides this, the weekend days are added as predictors for initial class membership. This model describes transitions in activity-travel patterns after all COVID-19 measures, including WFH mandates, are lifted in the Netherlands.

[1] Depicted in Table 5.4 in Chapter 5

6.2.1. General trends

Average transition matrix

All classes[2] show negative and mostly significant parameters. However, nine constants become very high, pointing towards very sparse data for certain transitions. For the transition probabilities, these nine constants also do not have significant p-values. The fact that the parameters for the transitions are already relatively high does not present a good starting situation to add a decrease in WFH variable to interact with transitions[3]. Still, no convergence problems appear when estimating the model.

Table 6.4 shows that only two parameters are significant for the interaction of the decrease in WFH variable with transitions. The low mobility class (class 2) shows an increased probability of transitioning to the car commuter and AM user for other trips class (class 4). This transition makes intuitive sense. Next, car commuters (class 3) show an increased probability of transitioning to the low mobility class (class 2), which seems counter-intuitive. These counter-intuitive findings can be drawn back to the same reasoning given in Section 6.1.1 for the low-mobility class. However, overall the Wald statistic of the decrease dummy variable has a p-value of 1. Thus, the effects of a decrease in WFH on transitions in activity-travel patterns seem very diverse but generally minor.

Table 6.4: Parameters for the 2021-2022 transition model

		2022 class membership						
		1	2	3	4	5	6	7
2021 class membership		Car users fo many other trips	Low mobility	Car commuters	Car commuters & AM users for other trips	AM commuters	AM users for many other trips	Multi-modal users
1 Car users fo many other trips	Constant	0	**-2.45 (0.00)**	**-2.51 (0.00)**	**-1.78 (0.00)**	-5.35 (0.26)	**-2.73 (0.00)**	**-2.54 (0.00)**
	Decrease (ref.=no decrease)	0	1.19 (0.18)	1.29 (0.23)	-0.04 (0.97)	-1.43 (0.9)	-4.11 (0.68)	-4.16 (0.68)
2 Low mobility	Constant	**-1.92 (0.00)**	0	**-1.26 (0.00)**	**-2.49 (0.00)**	**-1.7 (0.00)**	-7.72 (0.43)	-8.6 (0.38)
	Decrease (ref.=no decrease)	-2.87 (0.72)	0	-0.13 (0.85)	***1.33 (0.09)***	-0.11 (0.89)	0.4 (0.98)	6.8 (0.49)
3 Car commuters	Constant	**-4.6 (0.04)**	**-3.5 (0.00)**	0	**-2.66 (0.00)**	**-2.1 (0.00)**	-8.76 (0.38)	**-3.11 (0.00)**
	Decrease (ref.=no decrease)	-0.97 (0.92)	**2.86 (0.05)**	0	-0.33 (0.97)	-3.75 (0.71)	2.9 (0.84)	-2.56 (0.8)
4 Car commuters & AM users for other trips	Constant	**-1.2 (0.00)**	**-4.28 (0.01)**	**-1.74 (0.00)**	0	**-2.49 (0.01)**	**-1.86 (0.00)**	**-2.33 (0.00)**
	Decrease (ref.=no decrease)	-0.86 (0.56)	0.1 (0.99)	-4.43 (0.66)	0	-3.21 (0.75)	0.31 (0.81)	-3.54 (0.72)
5 AM commuters	Constant	-8.33 (0.4)	**-2.37 (0.00)**	**-2.4 (0.00)**	-8.32 (0.4)	0	**-2.41 (0.00)**	**-3.81 (0.00)**
	Decrease (ref.=no decrease)	7.33 (0.46)	0.93 (0.51)	-3.35 (0.74)	2.43 (0.86)	0	1.59 (0.28)	2.51 (0.18)
6 AM users for many other trips	Constant	**-2.72 (0.00)**	**-3.91 (0.00)**	-8.47 (0.39)	-7.05 (0.47)	-3.92 (0.22)	0	**-3.4 (0.00)**
	Decrease (ref.=no decrease)	-2.53 (0.8)	1.54 (0.64)	7.21 (0.47)	1.9 (0.89)	-1.73 (0.87)	0	-2.19 (0.83)
7 Multi-modal users	Constant	**-1.62 (0.00)**	**-2.45 (0.02)**	**-2.97 (0.00)**	**-2.24 (0.00)**	**-2.63 (0.02)**	**-1.39 (0.01)**	0
	Decrease (ref.=no decrease)	-4.97 (0.62)	-4.08 (0.68)	-3.55 (0.72)	-4.35 (0.66)	-3.71 (0.71)	-0.67 (0.57)	0

P-values depicted in parentheses
Parameters p<0.05 are bold
Parameters p<0.1 are bold and italic

The following describes general trends in class size developments between 2021 and 2022 and the effect of a decrease in WFH on transitions between activity-travel patterns. Although the effect is statistically not significant, meaning the results cannot be inferred to the population, the effects exist in the sample of the 717 respondents. Thus, this section still presents the effects in the sample without drawing any hard conclusions.

The average transition matrix, Table 6.5, shows that all probabilities of remaining in the same class are higher for 2021-2022 than for 2019-2021, except for the low mobility class. Classes 3, 5 and 6 show very inert behaviour. The off-diagonal probabilities are similar to the 2019-2021 matrix, except that the probabilities of transitioning to the low mobility class reduce drastically. Transitions to the low mobility class mostly appear after a small or large increase in WFH in the previous model. Since hardly any cases with an increase in WFH are included in the sample for this model, it makes sense that the probabilities of transitioning to a low mobility class reduce drastically in this model.

[2] Due to diverging class sizes, the class numbering is different than in the previous model.

[3] Models with 5 and 6 classes were tested as well. However, only minimal improvements appear. Thus, for comparability with the first model, the 7-class model is kept.

Table 6.5: Average transition matrix 2021-2022

	2022						
	1	2	3	4	5	6	7
2021	Car users for many other trips	Low mobility	Car commuters	Car commuters & AM users for other trips	AM commuters	AM users for many other trips	Multi-modal users
1	**0.66**	0.07	0.07	0.11	0.00	0.04	0.05
2	0.08	**0.58**	0.16	0.06	0.11	0.00	0.01
3	0.01	0.06	**0.76**	0.05	0.08	0.00	0.03
4	0.16	0.01	0.09	**0.57**	0.04	0.09	0.05
5	0.02	0.08	0.06	0.00	**0.73**	0.08	0.03
6	0.05	0.02	0.03	0.00	0.02	**0.86**	0.03
7	0.10	0.04	0.03	0.05	0.04	0.14	**0.61**

Class sizes

Next, the most notable differences in class sizes, shown in Figure 6.3[4], are discussed.

The share of the low mobility class (class 2) decreases in 2022. The reasons may be twofold. Certain people decrease WFH and, thus, adopt patterns with more trips again. Also, the general travel activity may have increased as all COVID-19 measures are lifted, leading to fewer people adopting such a pattern. Next, car commuters (class 3) increase in share. This may signify that commute travel by car is bouncing back as more people go to the workplace again. Nonetheless, minimal reductions in the other two car classes (class 1 and class 4), which have more other trips appear as well. Next, strict active mode user classes (class 5 and class 6) increase shares in 2022. In line with expectations, the multi-modal user share (class 7) remains more or less constant in 2021 and 2022, thus it remains low.

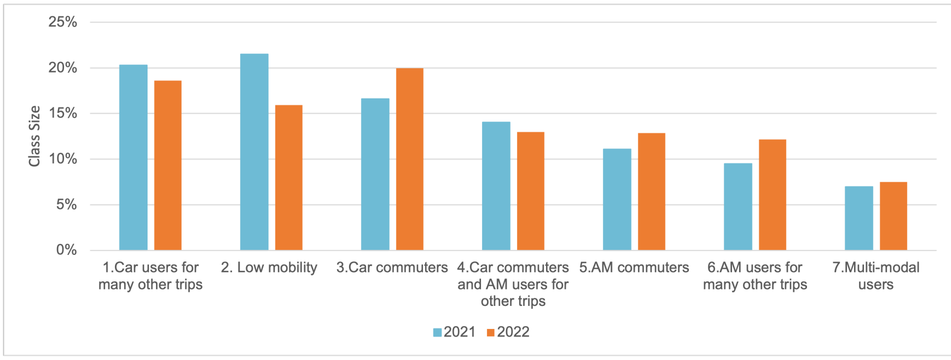


Figure 6.3: Share of activity-travel patterns in 2021 and 2022

6.2.2. Effect of a decrease in WFH on transition probabilities

Table 6.6 presents the transition matrices for the occurrence of no decrease or a decrease in WFH. The matrices, especially the one in Table 6.6 (3), are based on mostly non-significant parameters for a decrease in WFH. Thus, results and discussions need to be considered with care.

The probabilities in bold highlight the probability of remaining in the same class in the second year. Next, the colour shades in Table 6.6 highlight low probabilities to stay or transition in/ to a class in blue, while high probabilities are highlighted in red colour shades.

[4]The shares for 2021 slightly diverge from the ones shown in Figure 6.1 as a different sample is used.

Table 6.6: Transition matrix for the occurrence of no decrease or a decrease

		2021	2022 1 Car users for many other trips	2 Low mobility	3 Car commuters	4 Car commuters & AM users for other trips	5 AM commuters	6 AM users for many other trips	7 Multi-modal users
(1)	Average Transition Matrix	1	**0.66**	0.07	0.07	0.11	0.00	0.04	0.05
		2	0.08	**0.58**	0.16	0.06	0.11	0.00	0.01
		3	0.01	0.06	**0.76**	0.05	0.08	0.00	0.03
		4	0.16	0.01	0.09	**0.57**	0.04	0.09	0.05
		5	0.02	0.08	0.06	0.00	**0.73**	0.08	0.03
		6	0.05	0.02	0.03	0.00	0.02	**0.86**	0.03
		7	0.10	0.04	0.03	0.05	0.04	0.14	**0.61**
(2)	No decrease	1	**0.67**	0.06	0.06	0.11	0.00	0.04	0.05
		2	0.09	**0.59**	0.17	0.05	0.11	0.00	0.00
		3	0.01	0.02	**0.78**	0.05	0.10	0.00	0.04
		4	0.17	0.01	0.10	**0.55**	0.05	0.09	0.05
		5	0.00	0.07	0.07	0.00	**0.77**	0.07	0.02
		6	0.06	0.02	0.00	0.00	0.02	**0.88**	0.03
		7	0.11	0.05	0.03	0.06	0.04	0.14	**0.57**
(3)	Decrease by at least 8 hours	1	**0.57**	0.16	0.17	0.09	0.00	0.00	0.00
		2	0.00	**0.53**	0.13	0.16	0.09	0.00	0.09
		3	0.00	0.33	**0.63**	0.03	0.00	0.00	0.00
		4	0.09	0.01	0.00	**0.73**	0.00	0.16	0.00
		5	0.16	0.10	0.00	0.00	**0.43**	0.19	0.12
		6	0.00	0.07	0.20	0.00	0.00	**0.72**	0.00
		7	0.00	0.00	0.00	0.00	0.00	0.11	**0.88**

Probability to remain in the same class in bold

Transition/ stayer probabilities

Low **High**

After no decrease in WFH, Table 6.6 (2), the transition matrix shows roughly the same as the average transition matrix. This is due to the low frequency of decrease cases in the sample.

Decrease in WFH

After a decrease in WFH, Table 6.6 (3), certain transitions appear logical, while others are rather counter-intuitive. Given that only two estimates are significant for the decrease in WFH variable, the counter-intuitive findings should not be over-assessed. The numerous blue cells in the matrix show that many transitions have a probability of 0.

First, intuitive findings are discussed. Generally, the probabilities of remaining in the same class are lower than in the average transition matrix, except for car commuters and active mode users for other trips (class 4,) and multi-modal users (class 7). It seems logical that these two classes remain high, as both count many work trips. Car users with many other trips (class 1), show an increased probability of transitioning to class 3 and becoming car commuters again. Next, people in the low mobility class show an increased probability of becoming a car commuter, active mode user with many other trips (class 4), or multi-modal user (class 7). Furthermore, AM users for many other trips (class 6) show an increased probability of becoming car commuters (class 3). Generally, this last transition intuitively makes sense. However, this relation does not exist in the increase model. This may point towards an asymmetry in transitions for a decrease in WFH compared to an increase.

Counter-intuitively, transitions to the low mobility class appear after a decrease in WFH. In case of a decrease in WFH, one expects that people transition towards classes with at least some commute trips. Class 1, 3 and 5 show increased probabilities of transitioning. Especially car commuters (class 3) show a very high probability of 33 % to transition to the low mobility class, which is linked to a significant parameter in the model. Generally, these findings could point towards a decrease in working. However, large decreases in working are accounted for by cleaning the sample for this model. Thus, these surprising findings may again be due to similar reasons as for the previous model, discussed in Section 6.1.1.

Next, class 4, car commuters and AM users for many other trips have a higher probability of becoming an AM commuter. These classes count the same number of work trips but show a change in the commute mode. These findings could point towards a change in jobs, leading to using a different mode which was not accounted for in this research, and, thus, presents a limitation. Kroesen (2014) pointed out that a change in jobs can lead to reevaluating activity-travel patterns.

The probability of remaining an active mode commuter (class 5) is the lowest with 43 %, compared to 73 % in the average transition matrix. This class has an increased probability of becoming car users with many other trips (class 1), an active mode user with many other trips (class 6), or a multi-modal user (class 7). For a small increase in WFH, Table 6.3 (3), active mode commuters spread evenly to other classes. It is interesting to see this in this model again, although the opposite effect is studied. It seems that after a decrease in WFH, AM commuters start making more trips for non-work purposes again. One would expect that class 5, which is a commuter class, retains a high probability of remaining in their class just as other commuter classes (class 3, 4, 7). Class 4 and 7 even have a higher probability to remain in their class than in the average transition matrix, which seems logical. This could mean that commuting by active modes may generally be more variable from one measurement to another, depending on personal plans.

6.2.3. Effect of a decrease in WFH on class sizes

For completeness and comparability with the results described for the 2019-2021 model, the effect of a decrease on class sizes is also depicted in Figure 6.4 and discussed.

The effect of a decrease in WFH on class sizes also mirrors the logical and counter-intuitive findings. The counter-intuitive results linked to the low mobility class stand out through the large size of this class after a decrease in WFH. Nonetheless, this could also mean that many people are still working from home for a few days on which they are low mobile. Next, the multi-modal user share is remarkably higher than on average or without a decrease. This seems logical, as many people who adopted or increased WFH were PT commuters pre-COVID, Section 2.2.3. Furthermore, car commuters (class 3) bounce back to higher levels than before, but not for a decrease in WFH. Generally, after a decrease in WFH, classes with many overall trips (class 1 and class 6) slightly decrease in shares.

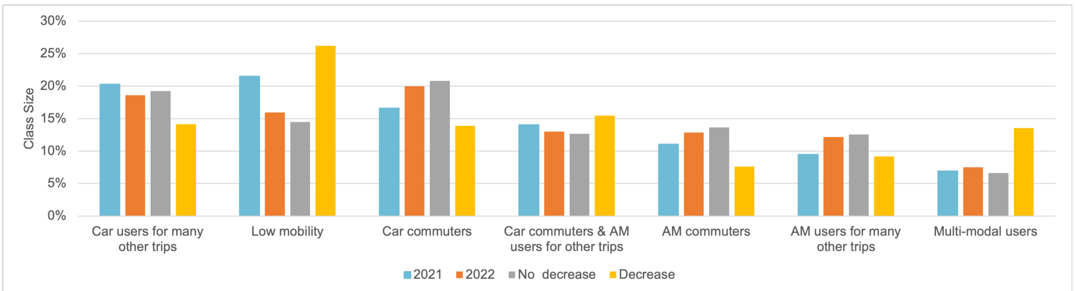


Figure 6.4: Share of activity-travel patterns after occurrence of (no) decrease

6.2.4. Discussion and conclusion

The result that the effect of a decrease in WFH is not statistically significant may mean four things: First, a sample of 717 wave pairs may be too small for a 7-state LTA, in which a variable interacts with transitions. The dataset may be too sparse for transitions from/to certain classes. This impacts the reliability of the transition matrices in this second model. Second, the frequency of a decrease in WFH may be too low to find statistically significant results. Third, the decrease variable may still be mixed up with other changes in the working situation. Fourth, there may indeed be no effect of a decrease in WFH on transitions in activity-travel patterns or only very diverse effects. Fifth, the elapsed time after relaxing COVID-19 measures may be too short to study a decrease in WFH and effects on activity-travel patterns.

The fourth option is particularly interesting. If no effect of a decrease in WFH exists, this means that WFH, even if only done temporarily more often during COVID-19, may have resulted in structural changes in travel behaviour. This points towards asymmetry between the effects of an increase and a decrease in WFH. Based on the sample in the second model, if people decrease their WFH extent to a more hybrid form or shift back to the workplace full-time (only a low number of cases), they do not shift back to their old activity-travel patterns as much as they changed to different patterns after an increase in WFH occurred. This observation in combination with the finding that the effect of an increase in WFH on transitions is significant while the effect of a decrease is not significant may point to a form of hysteresis or asymmetry.

In the travel domain, the concept of hysteresis has been shown for the effect of income on car ownership (Dargay, 2001). In this research, hysteresis would mean that the effect of an increase in WFH on activity-travel behaviour is not fully reversed if WFH decreases (Dargay, 2001). Causes for this phenomenon may be the creation of new habits, new routines and daily schedules, or task sharing with other household members while working from home leading to lasting adaptations in activity-travel patterns. The first model, for an increase in WFH, showed no unique relationship exists between an increase in WFH and activity-travel patterns. Transitions depend on initial class membership and, thus, diverge between classes. The existence of hysteresis complicates this relationship for a decrease in WFH. Thus, the consequences of an increase in WFH should not be used to conclude what happens when people return to the workplace. If hysteresis exists in this case, assumptions based on a reverse effect of an increase would be misleading. Also, Chapter 4 already showed that the observed frequencies of decreases in WFH between 2021-2022 are not excessively high. This may mean that many employees have already found their hybrid optimum between WFH and the workplace around September-October 2021. In this sense, a certain form of asymmetry may make sense as many people do not return to their status quo working at the workplace. It can be that somebody increased his WFH status to full-time in the first model and only decreased it by 1-2 days in the second model. Thus, the nature of increases and decreases can explain observed asymmetry. Nonetheless, remaining WFH levels point towards a structural change in how people work. Actual hysteresis would mean that the WFH experience leads to structural change in activity-travel behaviour, which is not fully reversed. It remains to be seen whether created habits are difficult to reverse in this case. Long-term trends still need to be investigated.

Nonetheless, this reflection needs to be savoured with care, as both models are not based on exactly the same sample and operationalisation. The sample of the second model is mostly a sub-sample of the first, and class profiles slightly change. Further research should investigate this matter for exactly the same sample and class profiles and similar increase/ decrease levels. Thus, no hard evidence exists yet, and the non-significant results can also be related to the other explanations mentioned above.

Although the results of this model are not statistically significant, general insights into transitions in activity-travel patterns and the reallocation of class shares in 2022 are gained. Overall, the low mobility share decreases and car commuter shares increase in 2022, while the multi-modal class remains small in size. Decreases in the low mobility share and increases in the car commuter share seem intuitive as people work at the workplace more frequently again. Nonetheless, small multi-modal shares remain worrying as the car seems to be the preferred mode. These insights signal important findings for policymakers.

7

Discussion and conclusion

This chapter first provides an answer to the sub-questions leading to an answer to the main research question in Section 7.1. Next, it reflects on the research while comparing the findings to existing research in Section 7.2. After that, the policy implications related to the findings are presented and discussed in Section 7.3. Next, the limitations are elaborately discussed in Section 7.4. Finally, Section 7.5 concludes with recommendations for further research.

7.1. Answer to research questions

1) What are the conceptual relations between WFH and activity-travel patterns during the pandemic?

To answer this sub-question COVID-19 travel behaviour change, WFH development in the Netherlands and general WFH and travel literature has been selected and analysed. The building blocks of this conceptual model are a change in WFH, commute travel, other non-work travel, mode use, individual characteristics and COVID-19 measures, depicted in Figure 7.1. Commute travel, non-work travel, and mode use together define activity-travel patterns in this research.

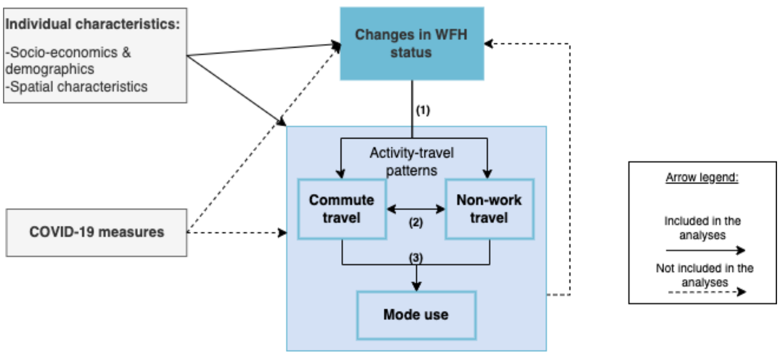


Figure 7.1: Conceptual relations between WFH and activity-travel patterns

The conceptual model synthesizes three important relationships from literature. First, WFH impacts travel for different purposes: commute and non-work travel (1). For example, the number of commute trips is expected to decrease when adopting full-day WFH. Next, the relationship between activities, commute and non-work travel is included (2). One possible relationship may be that the reduction in commute trips favours an increase in travel for non-work purposes. Furthermore, an indirect relationship between WFH and mode use (3) running through activities is depicted. For instance, WFH may reduce the use of specific modes, such as PT. However, this is due to the elimination of commutes.

Next, individual characteristics, such as socio-demographics, economics, and spatial variables, are found to influence WFH and activity-travel patterns. Moreover, COVID-19 measures also influence both a change in WFH and activity-travel. Nonetheless, COVID-19 measures are only included with dotted lines. As these measures held at a national level, they can be considered a constant in this research. It is hypothesized that people with a change in WFH still change their activity-travel patterns differently or more extremely than people without a change in WFH, as these people still need to engage in commute travel.

The direction of causality was prominently discussed in general WFH and travel literature. However, this research assumes an effect of a change in WFH on activity-travel patterns. WFH was a policy measure at a national level. Thus, it is defensible to assume an exogenous effect on travel. Nonetheless, to acknowledge complexities in the relationship between a change in WFH and travel, dotted lines running from activity-travel to a change in WFH are depicted. For instance, literature found that people who commuted pre-COVID-19 by PT were more prone to adopt WFH. However, this may also be due to individual characteristics of this traveller group, such as high educational levels. These reverse effects have not been further considered in this research, which presents a limitation of this work. Thus, relationships presented by dotted lines are not actively included in this research.

To study the effect of a change in WFH on transitions in activity-travel patterns, a change in WFH variable needs to be defined. For this purpose, the second sub-question is phrased as follows:

2) What changes in the extent of WFH emerged during the pandemic?

Recent research studying the effect of WFH on travel did not study the impact of a change in WFH status on transitions in activity-travel patterns. A change in WFH variable needs to be defined to achieve the objective of this study.
For 2019-2021, as expected, many people increased their working from home extent. Increases of different magnitudes appeared, many smaller increases by 8-23 hours and numerous large increases by at least 24 hours per week. This is in line with the general trend that many people adopted WFH full-time during the pandemic. For 2019-2021, the study of a decrease in WFH is not insightful due to extremely low frequencies of decreases in WFH. Beyond this, a decrease in WFH is primarily due to a decrease in working, not a decrease in WFH. Thus, it is decided to keep the models of this research more parsimonious by studying two different models and by merging the decreases with no change in WFH for 2019-2021. For 2021-2022, more decreases in WFH are observed, likely because people transitioned to more hybrid working forms after the WFH advice no longer held. These decreases are primarily due to a decrease in WFH and not a decrease in working. For 2021-2022 wave pairs, the frequencies for an increase in WFH above 7 hours per week are relatively low. Here increases are merged with cases without a decrease in WFH. Thus, to keep the models parsimonious and meaningful, it is decided to estimate two separate models: One model for 2019-2021 studying the effect of an increase in WFH and one model for 2021-2022 studying a decrease in WFH. The differences in sample sizes for the wave pairs, N=1774 for 2019-2021, and N=717 for 2021-2022 further back up this choice.

Thus, an increase and a decrease in WFH variable need to be defined. The definition of an increase in WFH is based on the policy relevance, existing empirical research and descriptive data analyses. As employees expect to work from home for 1-3 days post-pandemic it is differentiated between a small and a large increase in WFH. The intervals are set based on the data distribution for an increase in WFH. An increase in WFH variable is defined as follows on an ordinal scale:

1. **No increase:** Representing no change in WFH, an increase of less than 8 hours and all decreases.
2. **Small increase in WFH:** Representing an increase by 8-23 hours WFH per week, thus, an increase by probably less than 3 full working days but at least 1-2 working days.
3. **Large increase in WFH:** Representing an increase by at least 24 hours, thus, probably at least 3 or more days.

For a decrease in WFH, not many large decreases in WFH existed in the data. Thus, as a matter of simplification a decrease is defined as a decrease by at least 8 hours. A decrease is defined by an ordinal variable with two levels:

1. **No decrease:** Representing no change in WFH, a decrease of less than 8 hours per week, or an increase of any kind.
2. **Decrease:** Representing a decrease by at least 8 hours per week.

For both variables, the strict intervals based on the hour counts present a limitation of this research. However, this is generally a limitation of the dataset as the exact number of days respondents worked from home is unavailable.

Most existing WFH and travel studies did not investigate all forms of personal travel. They did not consider multiple activities and modes simultaneously when studying the impacts of WFH on travel. Thus, these activity-travel patterns need to be identified first.

3) What activity-travel patterns did workers adopt in the Netherlands throughout the pandemic?

Self-reported trip rates define activity-travel patterns based on trip purposes and modes. Three modes, car, public transport (PT) and active modes (AM) and two purposes, commute trips, defined as to/from work trips and other non-work trips, together form six indicators to define activity-travel patterns: to/from work car, to/from work PT, to/from work AM, other trips car, other trips PT, other trips AM. The application of Latent Class Analysis reveals seven activity-travel patterns. It must be noted that the LCA is estimated each time for two years simultaneously to identify the patterns. Figure 7.2 depicts the definition of the seven activity-travel patterns for 2019-2021, and Figure 7.3 for 2021-2022.

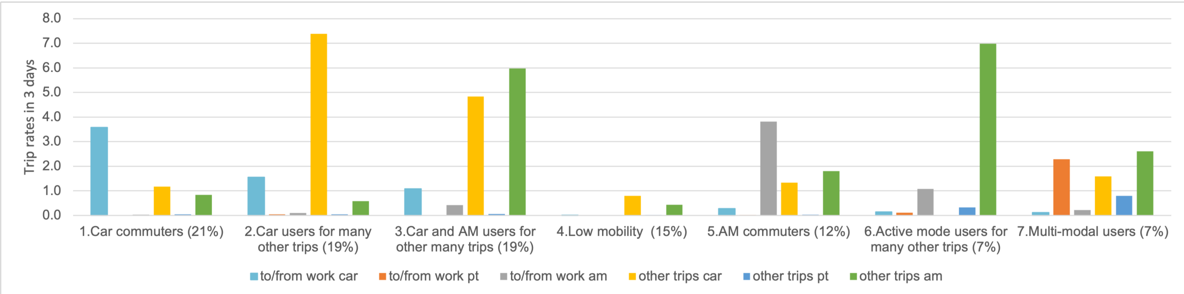


Figure 7.2: 7 Activity-travel patterns 19-21

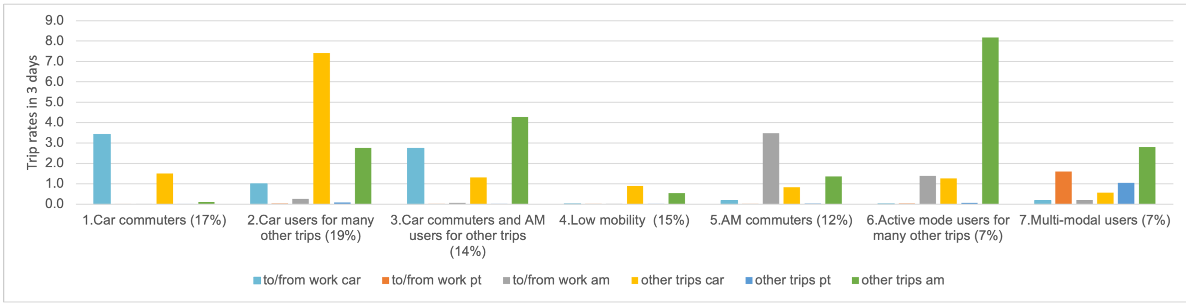


Figure 7.3: 7 Activity-travel patterns 21-22

The first class are car commuters, these travellers mostly take work trips by car, on average 3.5 (3.4) trips in three days. The second class are car users for many other trips, namely 7.4 trips for other purposes by car. The third class are AM and car users for many other trips in 2019-2021, with 4.8 trips by car and 6 trips by active modes. In 2021-2022, this class changes the absolute values on the indicators leading to being labelled car commuters and active mode users for other trips. The fourth class is a low mobility class which hardly counts any trips. The fifth class are active mode commuters with 3.7 (3.5) commute trips by active modes. The sixth class are active mode users for many other trips, counting 6.9 (8.2) other trips by active modes in three days. The final class are multi-modal users commuting by PT, with 2.1 (1.5) PT commutes in three days. Also, for each class, the mean distances travelled per purpose and mode in three days correlate with the trip rates, the indicators. Thus, the classes, based on trip rates, can still inform about the sustainability of the activity-travel patterns.

The comparison of patterns for both year pairs reveals that the identified patterns slightly change. 6 out of 7 classes remain the same, but the profile of class 3 qualitatively changes, although still keeping the same modes. Hence, although many respondents of the 2021-2022 sample were also present in 2019-2021, qualitatively identical patterns do not emerge. This points towards instability of identified patterns. This can be traced back to two reasons: a change in the sample size and composition or the evolving context and, hence, eventually evolving activity-travel patterns.

Cross-sectionally, the findings of the LCAs show that a substantial share of low mobile people and active mode users for many other trips work from home a lot. Covariates reveal these findings in both LCAs, for the 2019-2021 and the 2021-2022 data.

After identifying seven activity-travel patterns for 2019-2021 and 2021-2022, transitions between these patterns are evaluated. The main objective of this research is to assess the effect of a change in WFH on transitions in activity-travel patterns.

4) Which changes in WFH influence transitions in activity-travel patterns over the pandemic?

Chapter 6 presents two transition models to conclude on the effect of a change in WFH, an increase and a decrease in WFH, on transitions in activity-travel patterns. Results show that an increase in WFH has significant effects on transitions in activity-travel patterns for 2019-2021. Whereas no significant effects of a decrease in WFH are found for 2021-2022.

For an increase in WFH, two increase levels, a small and a large increase, are distinguished. More classes showed increased probabilities to transition for a large increase than after a small increase. Nonetheless, people are less inert after a small increase than when no increase occurs. Generally, the probability of transitioning to another class after an increase in WFH varies based on initial activity-travel patterns.

After a decrease in WFH, effects on transitions in activity-travel patterns are overall not significant. Also, the analyses of effects based on non-significant parameter estimates lead to partly counter-intuitive findings. The non-significant results for an effect of a decrease in WFH may primarily mean three things: First, the sample size may have been insufficient to estimate a 7-state LTA in which a variable interacts with transitions. Second, the frequency of a decrease in WFH may be too low to find statistically significant results. Third, there may indeed be no effect of a decrease in WFH on transitions in activity-travel patterns. Suppose no effect of a decrease in WFH exists. In that case, this means that WFH, even if only done temporarily more often during the pandemic, may have resulted in structural changes in travel behaviour. This points towards asymmetry between the effects of an increase seen for 2019-2021 and a decrease in WFH for 2021-2022. Based on the sample in the second model, people who decrease their WFH extent to a more hybrid form or shift back to the workplace full-time, do not shift back to their old activity-travel patterns as much as they changed to different patterns when an increase occurred between 2019-2021. This may be explained by the fact that not many large decreases occurred. The fact that not many decreases in WFH were found between 2021 and 2022 may mean that many employees already found their hybrid optimum between WFH and the workplace around September-October 2021. Against this background, the choice of MPN waves is critically assessed in the limitations in Section 7.4.

Having answered all the sub-questions the main research question can be answered.
How did changes in WFH influence activity-travel patterns during the pandemic in the Netherlands?

First, for 2019-2021, the impact of an increase in WFH is assessed, accounting for a small and a large increase. Second, for 2021-2022, the impact of a decrease in WFH, without making a difference in decrease levels, due to data availability and model parsimony, is assessed.

For an increase in WFH, may it be a small or a large increase, significant effects exist. Thus, an increase in WFH by at least 8 hours influences transitions in activity-travel patterns. For an increase in WFH, the results show that more respondents change their travel behaviour after an increase, except if already part of the low mobility group, or if already belonging to the AM users with many other trips, compared to the average. Thus, the effect of an increase in WFH on transitions is isolated by comparing people with an increase to people without an increase in WFH. People without an increase in WFH are the most inert, having the highest probability of keeping their initial activity-travel patterns. After a small increase, all classes except the AM users with many other trips become less inert. Thus, they show relatively lower probabilities of remaining in the same class.

After a small increase in WFH, the shares of the low mobility and AM profile class rise. However, car profiles remain very high or rise as well. This points towards very mixed effects after a small increase in WFH. After a large increase in WFH, car and AM commuter classes decrease drastically, which is beneficial for the low mobility, AM user, and multi-modal classes. Thus, more sustainable classes rise in shares. High shares in low mobility point towards substitution, exactly one-third adopts a low mobility pattern, while high shares in active modes point towards complementarity, modification or neutrality. Generally, high shares in low mobility after a large increase in WFH points towards sustainable and accessible travel behaviour from a transport perspective. In conclusion, the effect of WFH differs based on the increase in WFH level.

Next, the findings show that initial activity-travel patterns matter for transitions and, thus, the effects WFH has. For instance, car and AM users with many other trips (class 3) and AM mode users with many other trips (class 6) behave fundamentally differently than other classes. They have comparatively low probabilities of becoming part of the low mobility class, which may point towards underlying characteristics of these classes to have a higher trip demand in general. After a large increase in WFH car and AM users with many other trips (class 3) show a very high probability (30 %) of becoming AM mode users with many other trips (class 6).

The results for a decrease in WFH are not significant. Thus, no hard conclusions are drawn. Nonetheless, based on the sample in the second model, people do not shift back to their old activity-travel patterns after a decrease in WFH as much as they change to different patterns after an increase in WFH. Additionally, the fact that an increase in WFH leads to significant effects while a decrease to non-significant effects on transitions in activity-travel patterns may point towards asymmetry or hysteresis of a change in WFH on activity-travel patterns. Hysteresis would mean that the effect of an increase in WFH on activity-travel patterns is not fully reversed if WFH decreases (Dargay, 2001). Causes for this phenomenon may be the creation of new habits, new routines and daily schedules, or task sharing with other household members while working from home leading to lasting adaptations in activity-travel patterns. Nonetheless, further research is needed to confirm or deny this assumption, given the sample limitations of the second model. For the time being, these findings do not exclude the existence of structural changes in working and travel behaviour.

In conclusion, the results of this research lead to theoretically novel findings. The application of LTA, a longitudinal clustering method, sheds light on complex transition behaviour in the population during- and post-COVID-19 measures. The results of this research show that the initial class membership, thus, the activity-travel patterns before a change in WFH, and the level of an increase in WFH matter for the impact of WFH on transitions. To a certain extent, all effects of WFH on travel, substitution, complementarity, modification and neutrality exist in the population, but these depend on initial class membership. Thereby up to date, undiscussed heterogeneities in adapted travel behaviour which appear when increasing the working from home extent are uncovered.

7.2. Discussion

This section reflects on the findings and the methodology of this research and, where appropriate, compares them with existing literature. First, the empirical and theoretical findings are reflected on and discussed against existing literature. Second, a reflection on the stability of the findings for a post-pandemic context is given. Third, the usefulness of clustering methods for the general WFH and travel literature is briefly discussed.

Empirical and theoretical reflection
Cross-sectionally, the description of the activity-travel patterns reveals that WFH a lot is strongly associated with being low mobile or taking many trips by active modes for non-work purposes. This confirms the expectation that at least for a certain share in the population WFH is associated with a lot of travel by active modes (Chakrabarti, 2018; de Abreu e Silva & Melo, 2018; Elldér, 2020; Lachapelle et al., 2018). Generally, both findings also confirm and update recent findings by Elldér (2020) that people who work from home travel less in total but more by active modes. However, by studying comprehensive activity-travel patterns, this research also reveals that these relations do not necessarily hold for the same individuals. Some people who work from home have minimal overall personal travel for all modes and purposes, while others travel a lot by active modes for non-work purposes. Reflecting on this finding, low mobile behaviour uncovers a potential concern for physical activity. Since previous research did not investigate comprehensive activity-travel patterns formed by multiple modes and activities, such insights remain hidden until now. Thus, while lower travel demand benefits the transport system, it must be critically assessed against physical activity. WFH and travel behaviour studies should further include physical activity in their research, as done by Chakrabarti (2018) and Lachapelle et al. (2018).

Longitudinally, the results of this research lead to theoretically novel findings by shedding light on complex transition behaviour in the population during and post-COVID-19 measures. The following findings are reflected on in-depth:

- **Different effects based on past travel behaviour:** Based on initial activity-travel patterns, all effects of substitution, complementarity, modification or neutrality exist to some extent. Thereby, up-to-date, undiscussed heterogeneities in adapted travel behaviour are uncovered.
- **Different effects based on WFH levels:** The level of an increase in WFH leads to distinct effects on transitions in activity-travel patterns.

Different effects based on past travel behaviour:
Established research studying changes in travel behaviour after the adoption of WFH, based on longitudinal data, only found results pointing towards substitution in commute trips, non-work trips and trips by all modes (Hamer et al., 1991; Kitamura et al., 1990; Mokhtarian, 1991b). However, these results hid the exact nature of intra-personal change as only averaged results were presented. The results of this research show strong evidence that different transitions occur depending on the travel behaviour before a WFH increase. Certain people seem to have inherently more active lifestyles than others which also remain after adopting WFH, while a majority reduce travel. Travel behaviour research commonly acknowledges that past travel behaviour is predictive of future travel behaviour (Kroesen, 2014). This work is the first to actively include distinctions in past travel behaviour when investigating the effect of WFH on travel behaviour. Many WFH and travel behaviour studies likely did not include this due to unavailable longitudinal panel data (Caldarola & Sorrell, 2022; Elldér, 2020).

Nonetheless, this longitudinal before-after study reveals that many people adopt patterns that reduce their trip rates for work and other non-work purposes when increasing WFH. Thus, this is still in line with existing longitudinal research based on old datasets from pilots, pointing towards substitution of WFH for both work and non-work travel after adopting WFH (Kitamura et al., 1990; Hamer et al., 1991; Mokhtarian, 1991b).

The findings do not show strong overall evidence for a non-work travel rebound after increases in WFH. Nonetheless, such generation of travel exists at an individual level. After a small increase in WFH, transitions towards becoming a car user with many other trips are significant, pointing towards complementarity. However, class shares show that the net effects are likely balanced out. In contrast, recent research repeatedly finds complementarity effects of WFH on non-work travel comparing the trip rates of WFH and non-WFH people (Budnitz et al., 2020; He & Hu, 2015). Recent studies did not use longitudinal data to study changes in travel related to WFH. The findings of this research, based on a before-after study, seem to argue in favour of the theory that revealed differences in past studies may stem from unobserved heterogeneity between people who work from home and those who do not, and not from WFH per se (Caldarola & Sorrell, 2022; Mouratidis et al., 2021). Pre-COVID-19, people working from home self-selected themselves, and these people likely had inherently different travel demand (He & Hu, 2015; Mokhtarian et al., 2004). In contrast, people in the sample of this study were forced to work from home or suddenly able to do so which likely influences the results of this research.

Further reflecting on these findings and attempting to classify the results of this research against the SCMN-classification, one could argue: All forms of SCMN exist in the population. Certain transitions pointing towards modification or neutrality, remaining in the same class, are also revealed. These findings lead to agreeing with a reflection by Elldér (2020). The widespread substitution-complementarity lens can be problematic. In his pre-COVID-19 study, he stressed that WFH is a complex coping mechanism used in different ways by different people. Using a person-centred method, the research at hand shows that mixed results exist in the same sample. Hence, existing studies overshadow the exact nature of change that occurs when increasing WFH. The use of variable-centred methods leads to averaged results. These methods still fulfill their purpose of showing associations and main trends. However, differences between subgroups remain hidden, leading to overall conclusions.

Different effects based on WFH levels:
Next, this research found different effects for a small and a large increase in WFH. From a transport perspective, a large increase seems more beneficial, due to high reductions in travel demand given low mobile behaviour. The differences in impacts based on increases in WFH levels partly parallel findings in existing literature. Elldér (2020) found that full-day WFH reduces travel demand while part-day WFH people make more trips and travel further distances. Also, the results of this research show that a small increase in WFH has less positive and somewhat mixed effects on the transport system since car profiles remain very popular compared to large increases in WFH. Similarly, Caldarola and Sorrell (2022) found that people working from home for 1-2 days travel more for private travel than people who work from home for at least three days. Comparing class shares after small and large increases in WFH, this research shows similar findings. Thus, agreeing with Elldér (2020) and Caldarola and Sorrell (2022), it is essential to differentiate between different WFH arrangements or intensities in future studies since the travel impacts show to be very different.

Reflection on the stability of the findings for a post-pandemic context
Finally, other COVID-19 measures, potential hysteresis, and long-term effects of WFH on activity-travel make it challenging to conclude about the stability of results in a post-pandemic future. First, reductions in mobility, and substitution effects, found for both a small and a large increase in WFH may have coincided with other COVID-19 policies. Still, as a strong association between WFH and the low mobility class appears for both cross-sectional analyses 2019-2021 and 2021-2022, WFH seems strongly related to travelling less. Second, working from home levels will likely be lower than during peaks in the pandemic but structurally higher than pre-pandemic. Based on the findings and limitations of the second model, it is difficult to say how the new cohort of people who work from home will travel in the *’new normal’* post-pandemic. The potential existence of hysteresis between the effects of an increase and a decrease in WFH makes it challenging to assess how far the results of this research hold for the future. Third, uncertainties are further amplified by theoretically acknowledged endogeneity of WFH. In the long-term post-pandemic self-selection and the critical question of causality will become crucial again. People who enjoyed working from home during COVID-19 and live further away may work from home more than people living in workplace proximity. Besides, old research hypotheses about long-term effects of WFH, such as moving closer to a partner’s workplace or accepting a job further away, given WFH options gain a new importance midst and post-pandemic (Mokhtarian, 1991b). Many companies started promoting attractive fully remote or hybrid vacancies due to the pandemic, which likely makes the study of the relation between WFH and travel and eventual rebound effects even more complex. Thus, self-selection, work, and residential location will again be essential phenomena to study in the future.

Clustering methods for WFH and travel behaviour studies
This research shows multiple important methodological contributions, in terms of method and data use, discussed and reflected on below.

This study appears to be the first to apply a clustering method to study the impact of WFH on travel. On the one hand, this allows identifying the effects of WFH on all forms of personal daily travel simultaneously. On the other hand, this uncovers the exact nature of change occurring after adopting WFH, which remains hidden when studying the aggregate effects of WFH on travel with variable-centred methods. The latter is linked to the availability of longitudinal data. Thus, the novel findings mentioned above can essentially be uncovered thanks to the application of latent class and the longitudinal extension, latent transition analysis. In summary, the findings of this study speak in favour of using clustering methods in this field of study to understand heterogeneous trends in travel behaviour related to WFH next to averaged results. Doing so allows further revealing underlying complexities that remain hidden in existing research.

Generally, the availability of longitudinal data seems to be scarce for WFH and travel behaviour studies (Caldarola & Sorrell, 2022; Elldér, 2020). Since all recent WFH and travel studies, reviewed in Section 2.3.3, used (repeated) cross-sectional data, possibilities for using clustering methods on cross-sectional data are presented. Reflecting on the results of this research, insights about shares of activity-travel patterns after a change in WFH can also be achieved with cross-sectional data. Existing WFH and travel studies compared the travel behaviour of people who work from home to the behaviour of people who do not. Grouping people with a change in WFH and those without and running a latent class analysis still allows to show the different shares in activity-travel patterns. Besides this, LCA can be used to study the impact of WFH on class membership. While this is only briefly done to describe activity-travel patterns in Section 5.1, this could also form a research on itself. Furthermore, repeated cross-sectional data can be used to assess the stability of results related to WFH and travel over time, as done by Zhu (2012). While this delivers insights about evolving trends in the population, this does not deliver insights about intra-personal changes. For this purpose, longitudinal data remains necessary.

7.3. Policy implications

This section describes and reflects on policy implications directly following the results of this research. Chapter 1 introduced WFH as a potential policy-lever for more sustainable and accessible transport. However, knowledge on the effects of WFH on overall personal daily mobility is missing. Against this background, this research has analysed the effect of a change in WFH on comprehensive activity-travel patterns defined by two purposes and three modes. Transitions between classes and class shares after changes in WFH lead to the policy implications discussed below.

After a small increase in WFH, both positive and negative effects emerge compared to no increase in WFH. On the one hand, people adopt low mobility behaviour and use active modes for many other non-work trips. On the other hand, some people become or stay car users with many other trips. Overall shares in car users are relatively high after a small increase in WFH. These findings show that for large parts of the population, a small increase in WFH does not lead to less travel, especially not less travel by car. Many car trips lead to engine cold starts independent of the travelled distances. Research shows that about 80 % of emissions relate to the start of a vehicle and not its on-road time (Reiter & Kockelman, 2016). It may be expected that once more people adopt working from home for 1-2 days instead of the majority of their working week, car shares will exceed pre-COVID levels. The second model, studying post-COVID-19 measures data, supports the worrying car view since the share of car commuters bounces back to higher levels in 2022 compared to 2021. Nonetheless, it may be that these car trips occur in off-peak hours and, thus, still benefit the accessibility of the transport system.

If many people work from home and still drive a car for many trips, new avenues to manage travel demand are required. From an **employer** perspective, one option is to initiate a radical shift in commute travel programs such as lease cars or other mobility packages. Thus, employers should focus on carbonless commuting to steer away from a work-life that causes driving behaviour (Riggs, 2020). Another option could be not to offer commuting allowances anymore and by this stimulate people to live closer to their workplace.

Next, large increases in WFH mainly lead to low mobile activity-travel behaviour. This signals a reduction in travel, enhancing sustainability (less mobility) and accessibility (less crowding and congestion). As low mobile activity-travel behaviour generally means hardly any trips, one can confidently say that a large increase in WFH also relieves peak travel.

Thus, the transitions and overall class shares after increases in WFH show that the benefits of a small increase in WFH may be limited if overall personal mobility is analysed. After a large increase in WFH, actual reductions in travel are more apparent. Thus, purely relying on the results of this research, the government could be advised to stimulate large increases in WFH instead of small increases in WFH.

However, when pronouncing the beneficial effect of a large increase in WFH for the transport system, it must be kept in mind that this research only focused on the short-term. Long-term, current reductions in commute travel may be outbalanced by relocating to areas further away from the workplace or people making more non-work trips because they got used to the increased spatio temporal flexibility when working from home. Another reason may be that they readopt pre-COVID-19 trips, which may be missing in the data used in this study.

Besides this, the adoption of low mobile behaviour presents a worrying consequence of WFH, which is essential to be considered by policy-makers. For instance, the transition analysis shows that people commuting by active modes prior to an increase in WFH become low mobile when working from home. Thus, at an intra-personal level, transitions reveal worrying negative effects of WFH on activity-travel. While low mobility may be advantageous for the accessibility and sustainability of the transport system, it is detrimental to physical health. The **government and employers** should take measures to counter-act low mobile behaviour while working from home. Further research should investigate how employees can be encouraged to take active breaks or do necessary non-work travel by active modes on WFH days. Analysing and comparing the characteristics and lifestyles of people who show the desired behaviour may be one option to initiate such research. Further research with LCA can bring such insights since the cross-sectional analysis already revealed that active mode users for many other trips work from home a lot and live in urban areas. Thus, further analyses should include personal and spatial variables. Another worrying aspect of WFH for more than 3 days per week may be reduced social contacts and professional isolation, known to exist when working from home (Golden et al., 2008).

Next, this research also investigated a decrease in WFH, which allows first insights into possible structural changes in working and travel post-pandemic. While model results do not permit to draw hard conclusions, they still point towards asymmetry in transitions in activity-travel patterns. This indicates that people do not shift back to activity-travel patterns after a decrease in WFH in the same way as they did for an increase in WFH. Thereby, the findings do not rule out structural changes in travel behaviour post-pandemic. Hence, WFH during COVID-19 may indeed have lasting effects on travel behaviour. Future analyses are needed to see whether this is indeed the case.

General results for 2021-2022, independent of a WFH effect, reveal that in May 2022, PT shares remain low, and car shares increased compared to 2021. This shows that the effects of COVID-19 and increased WFH levels still exist for PT ridership. If PT services should be offered with the same service levels, this means a loss for **PT companies** as they do not make a profit with low demand. This may have two consequences: PT companies reduce their service to reduce their costs as they make less income, or the **government** allocates more subsidies to PT companies so that the same service can be offered. The latter is the more favourable option since further reductions in service levels may lead to even more decreases in PT use. Nonetheless, after a decrease in WFH, the multi-modal shares are higher compared to no decrease in WFH. People decreasing WFH levels may adopt PT as a commute mode again. Thus, chances are high that PT use bounces back to some extent in the future. These findings support structurally different work and activity-travel post-COVID-19. The government should further focus on stimulating shifts away from individual motorised modes to non-motorised modes or PT.

Reflecting on whether the government should stimulate WFH for transport reasons, only part of the problem is faced in this research. A small increase in WFH does not necessarily increase the sustainability of activity-travel patterns compared to large increases and accessibility insights remain inconclusive.

Nonetheless, a small increase in WFH is the realistic scenario, as only about 10 % of workers expect to work from home almost full-time (Hamersma et al., 2020). Hence, if the goal is to work from home for 1-3 days per week, some action perspectives appear from the results of this research:

- **From a sustainability perspective**, the insights after a small increase in WFH show that the net effects on sustainability may go towards zero. The government should further focus on stimulating modal shifts away from the car next to stimulating WFH. The results of the second model also show that car commuters bounce back in 2022, compared to 2021. This may be amplified by the encouraged use of individual modes during COVID-19. Also, concerning the profitability of PT, the government should stimulate shifts away from individual motorised modes towards non-motorised modes or PT, favouring sustainability.
- **From an accessibility perspective**, peak travel avoidance, which is the most highly anticipated benefit of WFH, needs to be investigated. Even if the net effects on sustainability may go towards zero, it may still be advisable to stimulate small increases in WFH for peak travel avoidance. Nonetheless, in the short term, a large increase in WFH shows to be already beneficial for accessibility. However, this comes with a trade-off in physical activity for many.
- **From a societal perspective**, the government and employers should take measures to counteract low mobile behaviour while working from home. Physical activity while working from home needs to be promoted. Thus, large increases in WFH may not be an optimal solution in light of physical activity and personal well-being. Further research must investigate these dimensions in depth to shape future WFH policies in society's best interest. In case of an increase in WFH by more than three days, counter-acting low mobility is a priority.

Generally, the analysis of transitions shows that people are less inert to keep their activity-travel patterns when an increase in WFH appears. Thus, an increase in WFH presents a window of opportunity for travel behaviour change. Hence, policymakers may use moments of increased WFH to stimulate additional changes in travel behaviour, such as modal shifts towards sustainable modes, since people are receptive to change in these moments.

Reflecting on the insights, the transition behaviour revealed in this research can inform policy-makers about adaptation behaviour for future pandemics or similar disruptions of the transport system which require a large scale adoption of WFH.

7.4. Limitations

Although insightful findings result from this research, the study bears multiple theoretical and methodological limitations. Taking the logical order of the research, limitations are discussed by critically assessing each step.

7.4.1. Conceptual model

Reflecting on the conceptualisation of this research, Chapter 2 describes that decades of research are still unsure about the causal relation between WFH and travel. Due to a lack of accepted theory in the study field and the exogenous shock of COVID-19, which initiated global increases in WFH, this research operationalises WFH as entirely exogenous to travel. Thus, this research takes the causal assumption that a change in WFH has an impact on transitions in activity-travel patterns and not vice-versa. However, WFH is a construct which confounds with many other dimensions of life, such as personal and spatial characteristics. Thus, past studies strongly advocate for endogeneity of WFH (de Abreu e Silva & Melo, 2018; He & Hu, 2015). For the short-term, not actively controlling for spatial and personal characteristics is defensible, similarly the ignorance of endogeneity. Nonetheless, future research should again account for an endogenous character of WFH.

7.4.2. Data and operationalisation

WFH and travel data in the MPN

The first limitation of the data used in this study is the ambiguous formulation of the WFH question in the MPN. Respondents are asked about their hours worked from home 'in a recent week'. Thus, whether the respondent worked from home for the indicated number of hours in the week of filling in the travel diary is unknown. Neither is it known whether the respondent worked from home on the days of filling in the diary. This limits the reliability of the WFH data used in this study and, thus, also the research results. Nonetheless, the use of general indicators for the WFH frequency, meaning no information about WFH on the travel diary day, is a common limitation for the majority of studies reviewed in Section 2.3.3.

Next, compared to other studies, this research used information from a 3-day travel diary, while other studies used 1-day or 7-day travel diaries (de Abreu e Silva & Melo, 2018; Elldér, 2020). Applying a 3-day diary, in which respondents get assigned three days to report their travel, leads to a trade-off. Either accepting that certain respondents reported their travel on 1-2 weekend days or reducing the sample by only selecting respondents without travel reported on weekend days. The latter would lead to approximately only 3/7th of the sample size. The latter is not chosen as large sample sizes are an important condition for LTA models. Thus, it is accepted that some people did not report their travel for working days. Nonetheless, research using 7-day travel data found that WFH also impacted travel on weekends, thus, on non-working days (Hamer et al., 1991). Against this background, the research results are still valuable, but they must be savoured with care.

Furthermore, controlling for the number of reported weekend days in the LCA, results show that weekend days have a significant effect on class membership. Consequently, people may be miss-classified regarding their work-related travel behaviour. Car users for many other trips, car and AM users for many other trips and the low mobility class showed the highest mean for reported weekend days. At the same time, these classes also showed high shares of working from home a lot. Thus, while reported weekend days may be a limitation, they may have been beneficial in identifying meaningful class sizes in both time points. Still, as the weekdays remain the same for each respondent in the MPN it can be assumed that the weekend days did not influence the transition analysis. However, the findings show that people who increased working from home transitioned to patterns with high weekend rates.

WFH and other life events

Existing research found that effects of WFH are more pronounced if other life events occur as well (Buitelaar et al., 2021). Thus, changes in WFH may be confounded with other life events. For instance, moving away and increasing WFH may have a different effect than just increasing WFH. The same holds for a change in jobs. In such cases, a reevaluation of activity-travel patterns is required (Kroesen, 2014). However, the sample selection does not account for occurrences of other life events, which may confound with some of the effects of WFH found in this research. It is dispensed on cleaning the sample based on the occurrence of life events, as this knowledge is only available for 2021 and not for the 2022 dataset. However, cleaning the sample based on changes in the working situation would be possible with the available data. In hindsight, it would be important to exclude respondents with changes in the working situation, be it working hours or the job itself, to avoid that these additional effects influence the results and, thus, bias transitions.

Operationalisation of activity-travel

During the operationalisation of the indicators for the LCA and LTA, business travel and trips by other modes are left out due to theoretical and technical limitations. Low occurrences in the data lead to favouring model parsimony over accuracy. Thus, the classes do not fully mirror all forms of personal daily travel. Additional analysis, including business travel and trips by other modes, shows that leaving out these travel metrics does not harm the models. Thus, an overestimation of classes can be denied. Nonetheless, further research should try to include these two dimensions of activity-travel as well if sufficient data is available. Especially the inclusion of business travel could reveal interesting, theoretically un-underpinned insights as shown by Zhu and Mason (2014) and Caldarola and Sorrell (2022). Next, using trip rates instead of distances limits the informative value on the sustainability of activity-travel patterns after an increase in WFH. Travelled distances are relatable to CO_2 emissions, which offers direct sustainability insights. This limitation is counter-acted by describing the profiles with the total mean distances and mean distances per mode and purpose. Findings show that distances correlate with the trip rates in this research.

Personal and spatial variables
Next, due to relatively small sample sizes for estimating complex models, this research does not actively control for individual characteristics such as personal or spatial variables. However, general WFH and travel literature repeatedly found significant effects for such variables (Elldér, 2020). Further research should make sure to include these variables.

Operationalisation of WFH
All studies reviewed in Section 2.3.3 possessed WFH information in terms of days. However, the MPN only provides the WFH hours per week. This makes it challenging to quantify the increases or decreases in WFH in days. Hours per week could capture different circumstances, which have different or ambiguous effects on WFH compared to full-day WFH. For instance, working overtime from home after a work day or moonlighting a second job from home could be included in these hours (Mokhtarian, 2021). Nonetheless, the descriptive analyses reveal that working from home mostly increased in counts of 8 hours, and it is assumed that the majority reported increases representing full 8-hour working days. To reduce the drawbacks of this operationalisation, future research should account for overall working hours and working from home hours to define a change in WFH variable if no exact data on WFH days is available.

Increase vs. decrease in WFH
Related to the previous point, the exact nature of an increase or a decrease in WFH is somewhat uncertain. It is critical to reflect on this since the results show that an effect of an increase exists while no significant effect of a decrease in WFH is found. In this context, the chosen MPN waves and behavioural trends require critical assessment. The effect of an increase in WFH is tested on a much larger sample, and the observed frequency of an increase in WFH is remarkably higher than for a decrease in WFH. Thus, the starting conditions concerning the data to study both effects are not comparable. Still, the observed frequencies of increases and decreases already reveal interesting insights. Relatively seen, more people experienced an increase in WFH in 2021 than a decrease in WFH in 2022. This already shows that structural changes in working from home persist for the time being.

Next, the selected during-COVID-19 time-point to test the effect of an increase was measured in September-October 2021. However, in March 2020, when the pandemic started, the WFH levels were the highest and, thus, higher than in 2021. In September-October 2021, some people likely already found their hybrid-working stability. Thus, the small increase in WFH likely already includes people working from home full-time in 2020 or at least at the beginning of the pandemic. Thus, they already decreased their WFH extent in 2021. However, this development is not captured in the models presented in this research. Thus, an increase relatively to the pre-COVID-19 situation in 2019 is assumed, but this increase probably already presents a decrease compared to an earlier moment in the pandemic.

Based on the sample in the second model, if people decrease their WFH extent to a more hybrid form or shift back to the workplace full-time, they do not shift back to their old activity-travel patterns as much as they changed to different patterns when an increase occurred. Related to the explanation above, it can be that somebody increased his WFH status to full-time in the first model and only decreased it by 1-2 days in the second model. Thus, the nature of increases and decreases can explain observed asymmetry or hysteresis. Nonetheless, the remaining WFH levels point towards a structural change in the working situation. Further research should continue the analysis of decreases in WFH.

Measurement invariance assumption
This research assumes full measurement invariance, meaning that the classes remain the same across different time points. However, considering the accumulation of COVID-19 travel behaviour articles, which underpin changes in travel patterns, the emergence of the same patterns may be debatable. Nonetheless, the goal of this research is not to identify activity-travel patterns but to study transitions between them. Additional analyses showed that if estimated for the separate time points, slight differences in absolute indicator values appear, but at the core, the patterns remain the same. Thus,

the assumption does not lead to a wrong model. On the one hand, it leads to less flexibility in fitting the model. On the other hand, interpretability, comparability and fewer parameters are gained. Thus, complete accuracy in the class definition is traded off for interpretability purposes.

7.4.3. Results

Comparability between transition models

Slightly different patterns limit the exact comparability between both transition models and, thus, the comparison of increase and decrease effects. Slightly different sample compositions and sizes may be at the root of slightly different activity-travel patterns. While the differences in activity-travel patterns may stem from the samples used, they may also point towards re-evaluating patterns at a population level. Estimating both models with the same samples can bring further clarity. Nonetheless, to the best of the author's knowledge, this research is the first to study activity-travel patterns based on modes and travel purposes simultaneously. Existing studies defined patterns only based on modes or only on activities (Kroesen, 2014; De Haas et al., 2018; Goulias, 1999). Thus, the simultaneous use may make the patterns less stable. Re-estimating the models with only modes or purposes as indicators could bring further clarity.

Generalizability of results to other contexts

The study results are not entirely transferable to other contexts or regions. First, while the context allows for a large-scale natural *'experiment'* to study the effect of WFH on transitions in activity-travel patterns, long-term post-pandemic developments may differ. It cannot be denied that certain COVID-19 measures still held in 2021, and 2022 was an early post-measures period. Thus, routines and habits adopted during extreme COVID times still coincide in the 2021 and 2022 data, which may affect the research results.

Second, the data for the study is retrieved from a Dutch travel panel. General WFH and travel studies already pointed out that the national context matters (Elldér, 2020). The Netherlands has a more developed cycling culture and infrastructure than many other countries, and the national COVID-19 measures diverged from other countries (De Haas et al., 2020). Besides this, the Netherlands show the second highest WFH shares pre-COVID-19. Thus, cultural barriers to adopting and maintaining WFH and certain active travel patterns may be lower than in other countries.

7.5. Recommendations for further research

Having concluded on this research, avenues for further research are presented.

First, related to a conceptual limitation of this research, the use of panel data to study developments in WFH and travel behaviour is recommended. Although causality is assumed in this research, causality and self-selection still present areas of debate in this body of literature. The new context in which more people work from home may present an opportunity to continue this research. While studying causality and self-selection may not have been a priority in the short term, it certainly becomes necessary post-COVID-19 measures. The literature review revealed a general lack of panel studies to bring insights into causality. This is an important endeavour, as general WFH and travel literature warns about long-term consequences, such as relocation to places further away from the workplace. In this regard, structural-equation models (SEMs) can help account for the endogeneity of WFH. Generally, using SEMs presents the advantage that complex structures, including direct, indirect and reverse effects, can be studied. Thinking back to the conceptual model of this research, such a model allows to include relationships that could not be studied with the chosen method. Although the exact nature of change will remain hidden, the actual effect of WFH on travel behaviour, or vice-versa, can be revealed. Also, SEMs allow accounting for past-travel behaviour when studying WFH and travel, which shows to be necessary.

Next, this study only uses three points in time, pre-, during- and post-COVID-19 measures data to study transitions in activity-travel patterns. However, as mentioned in the limitations, the increases and decreases defined in this study hide more specific developments. If enough data is available, it is interesting to show all the transitions and how people went through the pandemic, capturing all increases and decreases across time. Another option could be to dummify the changes in WFH in earlier time points and by this, include these experiences in the analyses. Related to multiple time points, an option to increase the knowledge of these developments could also be to study lagged effects. This allows studying how an earlier time point influences activity-travel patterns at later points in time and not only in the subsequent time point. By this, the memory of the LTA is not limited to the previous time point. Such insights could reveal the actual effect of experiences made while working from home during COVID-19 on travel.

Furthermore, post-pandemic research should investigate the effect or the relation of actual WFH levels and travel patterns. Given radical changes in the context, this study analysed a change in WFH. However, a certain level of stability in WFH is expected in the future. Thus, further research should focus on the actual WFH levels and related travel impacts. Investigating whether people remain in the low mobility class when working from home also over the long term is essential. Such insights could further approve or deny the potential benefits or disadvantages of stimulating WFH. Moreover, such insights could show whether the results of this study are biased due to the COVID-19 context. Furthermore, these future studies should deploy peak travel and travelled distances to gain useful insights into the sustainability and accessibility of different WFH levels.

Next, further investigations on the effects of potential decreases in WFH on travel behaviour are required to accept or deny the speculations about asymmetry or hysteresis of this research. In this regard, directly asking respondents about changes in their travel behaviour may be a viable option. This information is available in the MPN. This data should be analysed to shed light on the effect of a decrease in WFH. Comparing answers about changes after a decrease in WFH to the answers after an increase in WFH allows for analysing the potential asymmetry between transitions. Thus, this may help to conclude on structural changes in working and travel.

Generally, it is recommended to study the relation between WFH and travel with the MPN using LTA. Once the pandemic is over, the contexts of regular waves are probably stable again. This means that wave pairs can be pooled from multiple time points and transition probabilities can be restricted. This allows for using larger samples while deploying the benefits of panel data. An additional benefit is that recent MPN measurements include information on the days of WFH, by this, limitations related to the operationalisation of WFH can be overcome.

Overall, the use of latent transition analysis or clustering methods in future WFH and travel behaviour research is recommended. The method does not allow to conclude on the main effects of WFH, but otherwise, unobserved heterogeneity can be revealed. Thus, it is recommended to use such methods next to variables-centred methods to identify trends in subgroups in the population which remain hidden otherwise. This allows detecting otherwise overseen concerns. LCA and LTA do not explicitly show increases and decreases in travel, but they reveal whether people adopt fundamentally different activity-travel behaviour after a change in WFH. Thus, transitions between activity-travel patterns allow revealing the nature of behavioural change that emerges at an individual level dependent on past behaviour and the WFH situation.

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A

Appendix: Individual characteristics overview

The articles reviewed in Section 2.3.3, analysing WFH and travel, all controlled for personal and spatial variables as these showed to be strongly correlated with WFH and travel patterns in previous research (Elldér, 2020). No additional in depth review was conducted for these variables, except for the factors influencing the WFH adoption during the pandemic in Section 2.2.3.

Table A.1 lists the variables included by the existing studies reviewed in Section 2.3.3. This table serves as an input for the operationalisation in Chapter 4.

Table A.1: Individual characteristics overview

	Personal charactersitics							Household characteristics		Spatial variables	Travel parameters			
	Age	Gender	Education level	Income	Sector	Job function	Full-time/ Part-time working	Number of adults	Number of children (incl. age)	Neighbourhood characteristics	Distance	Mobility resources	Commute distance	Weekday
Ellder (2020)	x	x	x	x				x	x	x		x		
de Abreu e Silva and Melo (2018)	x	x	x	x		x	x	x	x	x	x	x	x	
Chakrabarti (2018)	x	x	x	x		x		x	x	x				
He and Hu (2015)	x	x		x		x	x	x	x	x		x	x	
Kim et al. (2015)	x	x		x		x		x	x	x		x		
Lachapelle et al. (2018)	x	x		x					x					x
Zhu (2012)	x	x	x	x		x			x	x		x		
Zhu and Mason (2014)	x	x	x	x		x			x	x		x		
Caldarola & Sorrell (2022)	x	x	x	x	x	x	x	x	x	x		x		
Ozbilen et al. (2021)	x	x	x	x			x		x	x		x		
Budnitz et al. (2020)	x	x	x	x		x	x		x	x		x		
Asgari and Jin (2017)	x	x				x		x	x			x		

B

Appendix: Sample representativeness

Table 3.6 depicts the characteristics of the workers in the study sample. However, to generalise the study results to the Dutch working population, the selected sample should be representative of this population. To assess the representativeness of the sample, data of the Dutch working population provided by Statistics Netherlands (CBS) is used (CBS, 2022). CBS defines the working population, as the employed labour force. According to CBS, individuals with paid work, independently of the working hours, form this population. The presented data usually concerns people between 15 and 74 years (CBS, 2022).

This definition only partially aligns with the sample selection of this study No explicit age range is fixed in the sample selection described in Section 3.2.4. The study includes everybody working for pay for at least 1 hour per week. For 2019-2021, the sample shows ages ranging from 18 to 84 years. Two respondents are somewhat outside the CBS age range, one with 74 years in 2019 thus 76 in 2021, and one with 82 years in 2019 and 84 year in 2021. For 2021-2022, the range is 17-77, only one person is outside the CBS range with 76 years in 2021 and 77 years in 2022. Given only minimal divergence, it is assumed that the figures are comparable to the CBS data.

As the working population is a rather specific sample, not all variables used in this research are available for comparison with CBS data. Either CBS does not present the data for the working population or the variables are not compatible with the data available in the MPN. For instance, data on household composition, coming close to the family cycle, for the working population exists in CBS. However, CBS does not consider the age of children when showing the household composition. Hence, these statistics are not comparable. Next, also the personal income is not compared, due to differences in the definition of this variable. Finally, CBS does not provide data on sectors but only on occupations, thus, sectors cannot be compared. The level of urbanization is not presented at all by CBS for the working population.

Hence, the representativeness of the sample is only assessed based on the working hours per week, the most applicable working situation, gender, educational level, age, and WFH status for the working population. While working hours per week, WFH hours per week and age are included as continuous variables in Table 3.6, the continuous variables are converted into nominal or ordinal variables to align with the scales used by CBS and by this judge on the represenativeness. As both wave pairs, 2019-2021 and 2021-2022, include the year 2021, this data of both wave pairs is compared to CBS data from 2021. The comparison of both samples of this research and the CBS data is presented in Table B.1.

Table B.1: Sample representativeness

		Wave pair 2019-2021 (2021)	Wave pair 2021-2022 (2021)	CBS (2021)
Working hours per week (%)	Part-time (less than 35 hours)	42.6	44.2	48.1
	Full-time (35 hours or more)	57.4	55.8	51.9
Most applicable work situation (%)	Self-employed entrepreneur	7.5	9.1	15.6
	Employed non-governmental job	74.1	75.8	84.4*
	Employed by the government	18.4	15.2	-
Gender (%)	Male	48.9	51	52.8
	Female	51.1	49	47.2
Education level (%)	Low	13.4	16.4	19.4
	Medium	38.5	43.7	39.2
	High	48.1	39.9	40.8
	Unknown	/	/	0.6
Age (%)	Up to 24 years	1.5	3.6	16.4
	25-34 years	17	17.5	21.1
	35-54 years	51.8	50.6	41.0
	55-64 years	26.9	26.3	18.4
	65+	2.8	2.1	3.0
				CBS (2020)
WFH (%)	Not WFH	50	53.2	59.0
	WFH	50	46.8	41.0

*No distinction between being employed for governmental or non-governmental job

Differences in the statistics between the study samples and CBS data most likely stem from differences in the definition of the working population. Generally, the representativeness of the sample appears acceptable, only the age stands out remarkably. Both samples used in this research, appear to severely underrepresent people up to 24 years. This is most likely due to sampling on the most applicable working situation, as explained in Section 3.2.4. In consequence, people who indicated to be a student as their most applicable working situation were not included in the sample, although many work part-time. CBS most likely includes working students in their figures. This problem could be avoided by also sampling on the working situation next to the most applicable work situation.

For the working hours per week, the CBS data shows a higher share of part-time workers than both study samples. This is likely due to differences in the variable definition. In CBS overtime and unpaid hours are not included in the figures, while the MPN data likely includes such hours (CBS, 2022). Thus, people classified as working full-time, 35 hours or more, may actually only be part-time workers according to their contract. Nonetheless, the shares are still somewhat comparable. Next, considering the most applicable work situation, the study sample shows an underrepresentation of self-employed entrepreneurs and an overrepresentation of employed people. Furthermore, the gender shares of the 2021-2022 sample are more aligned with the CBS data than the ones of the 2019-2021 sample. For the 2019-2021 sample, lower educated people are more underrepresented than for the 2021-2022 sample, and highly educated people are overrepresented. For the 2021-2022 sample, medium educated people are slightly overrepresented. For age, both samples of this study show the same trends, people up to 24 years are severely underrepresented compared to the Dutch working population. People aged 25-34 are still underrepresented, but a bit less. Respondents aged 35-54 and 55-64 are overrepresented compared to the CBS data. People of 65 years or older more or less align with the CBS data. For WFH, the most recent data dates back to 2020, the first pandemic year. For 2021, the samples of this study show an exact 50-50 distribution between people who work from home and those who do not. The share of people not working from home is higher in the CBS sample than in the study sample. Reasons for this may be the higher age ranges in both of the samples, and for the 2019-2021 sample the high shares of highly educated people in the sample. The KiM found that older people and the highly educated are more likely to work from home (Hamersma et al., 2020).

In conclusion, no statistical tests are required to conclude that the sample is not entirely representative of the Dutch working population. This may be due to slight differences in the definition of the working population, variable definitions, and the longitudinal design of this research. Due to panel mortality, people drop out from one year to another. Respondents are only included if present in two consecutive wave pairs, thus, although the MPN is a representative panel, the sample in this study is not fully representative. The fact that the sample is not entirely representative presents a limitation that needs to be acknowledged when discussing and reflecting on the results.

All things considered, the sample provides an acceptable picture of the Dutch working population except for the underrepresentation of people aged up to 24 years.

C

Appendix: Parameters of the 7-class LCA for 2019-2021

Table C.1: Parameters of the 7-class LCA for 2019-2021

Models for Indicators	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Cluster6	Cluster7	Wald	p-value
to/from work car	2.53	1.70	1.34	-4.13	0.00	-0.64	-0.81	1519.06	0.00
to/from work pt	-1.22	0.49	-1.11	-3.21	-0.59	1.31	4.33	803.74	0.00
to/from work am	-1.78	-0.66	0.75	-3.02	2.94	1.68	0.09	2072.27	0.00
other trips car	0.25	2.09	1.66	-0.13	0.37	-4.80	0.55	3550.40	0.00
other trips pt	-0.58	-0.51	-0.40	-1.30	-0.84	1.38	2.25	379.53	0.00
other trips am	-0.71	-1.06	1.25	-1.36	0.05	1.41	0.42	3971.84	0.00
Intercepts	Overall	Wald	p-value						
to/from work car	-1.26	22.57	0.00						
to/from work pt	-3.50	113.07	0.00						
to/from work am	-1.60	235.46	0.00						
other trips car	-0.09	0.09	0.76						
other trips pt	-2.48	519.60	0.00						
other trips am	0.54	422.92	0.00						
Model for Clusters	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Cluster6	Cluster7	Wald	p-value
Intercept	-0.38	-0.12	0.93	-0.11	0.24	0.65	-1.22	55.05	0.00
Covariates	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Cluster6	Cluster7	Wald	p-value
Weekend days	-0.33	0.35	0.32	0.21	-0.41	-0.02	-0.11	155.57	0.00
WFH hours per week	-0.04	0.00	0.02	0.04	-0.06	0.05	0.00	211.88	0.00
Working hours per week	0.04	0.01	-0.03	0.00	0.01	-0.04	0.02	122.24	0.00

D

Appendix: Activity-travel patterns 2021-2022

D.1. Model selection for 2021-2022

For 2021-2022 the same procedure was applied as for 2019-2021 in section 5.1.1. Table D.1 again shows that the BIC is only of limited value as it continues decreasing with each additional class. The reduction of L^2 gives the most useful indication to select the number of activity-travel patterns.

Table D.1: Model fit information for 1-10 LCM for 2021-2022

	LL	BIC(LL)	Npar	L^2	df	p-value	Reduction in L^2	Additional Reduction in L^2	Smallest class size	# significant BVRs (above 3.84)
1-Cluster	-14074	28192	6	12051	1428	0.00			100%	13
2-Cluster	-12622	25338	13	9147	1421	0.00	24%	24.1%	43%	7
3-Cluster	-11701	23548	20	7305	1414	0.00	39%	15.3%	30%	9
4-Cluster	-11263	22721	27	6428	1407	0.00	47%	7.3%	18%	8
5-Cluster	-10912	22072	34	5727	1400	0.00	52%	5.8%	14%	9
6-Cluster	-10664	21627	41	5231	1393	0.00	57%	4.1%	7%	4
7-Cluster	-10468	21284	48	4838	1386	0.00	60%	3.3%	7%	2
8-Cluster	-10307	21014	55	4517	1379	0.00	63%	2.7%	6%	2
9-Cluster	-10203	20857	62	4310	1372	0.00	64%	1.7%	6%	1
10-Cluster	-10130	20761	69	4162	1365	0.00	65%	1.2%	6%	3

Table D.1 indicates the additional reduction in L^2 in the last column. Starting from a 6-class model the additional reduction in L^2 falls below 5% and, hence, becomes very small with each additional class. After a 7-class model, the additional reduction falls below 3 %, suggesting that a 7-class model balances model fit and parsimony. Also here the 6-class and 7-class model could be compared. However, the 7-class model is chosen for comparability with 2019-2021. Nonetheless, Figure D.2 depicts the profile of the 6-class model.

Table D.2: Profiles of the 6-class model 2021-2022

	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Cluster6
Cluster Size	23%	21%	18%	16%	14%	7%
Class label	Car commuters	Car users for many other trips	Low mobility	AM users for many other trips	AM commuters	Multi-modal users
Indicators						
to/from work car	3.5	1.1	0.0	1.0	0.0	0.1
to/from work pt	0.0	0.0	0.0	0.0	0.0	1.6
to/from work am	0.1	0.2	0.0	0.8	3.6	0.2
other trips car	1.3	7.2	1.0	1.1	0.9	0.6
other trips pt	0.0	0.1	0.0	0.0	0.0	1.0
other trips am	0.7	2.8	0.5	7.2	1.6	2.8

Figure D.3 depicts the profile of the 7-class model. Going from a 6-class to a 7-class model, a new class formed by people using the car for commutes and AM for many other trips emerges. Compared to the 6-class model this leads to a reduction in class sizes for car commuters and for AM users for many other trips. This seems logical as the new class presents a combination of both.

Table D.3: Profiles of the 7-class model 2021-2022

	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Cluster6	Cluster7
Cluster Size	19%	18%	17%	14%	14%	10%	7%
Class label	Car users for many other trips	Low mobility	Car commuters	Car commuters and AM users for other trips	AM commuters	AM users for many other trips	Multi-modal users
Indicators							
to/from work car	1.0	0.0	3.4	2.7	0.2	0.0	0.2
to/from work pt	0.0	0.0	0.0	0.0	0.0	0.0	1.6
to/from work am	0.3	0.0	0.0	0.1	3.5	1.4	0.2
other trips car	7.5	0.9	1.5	1.3	0.8	1.1	0.6
other trips pt	0.1	0.0	0.0	0.0	0.0	0.1	1.1
other trips am	2.8	0.5	0.1	4.3	1.3	8.0	2.8

D.2. 7 Activity-travel patterns for 2021-2022

Active covariates are added to the 7-class model. Adding these active covariates only minimally changes the absolute indicator values of the class profiles, shown in Table D.4.

According to the Wald-statistic, all indicators, active covariates and model for clusters intercepts are significant. Statistically significant active covariates mean that, working hours, WFH hours and reported weekend days are significant predictors for class membership. Significant model for clusters intercepts indicate that in the population one would expect that the sizes of the 7 classes are different. All parameters are presented in Table D.5.

Table D.4: Profiles of the 7-class model 2021-2022 incl. active covariates

	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Cluster6	Cluster7
Cluster Size	19%	19%	17%	14%	13%	11%	8%
Class label	Car users for many other trips	Low mobility	Car commuters	AM commuters	Car commuters and AM users for other trips	AM users for many other trips	Multi-modal users
Indicators							
to/from work car	1.0	0.0	3.5	0.2	2.9	0.0	0.2
to/from work pt	0.0	0.0	0.0	0.0	0.0	0.0	1.6
to/from work am	0.2	0.0	0.0	3.5	0.1	1.3	0.2
other trips car	7.4	1.0	1.4	0.8	1.3	1.4	0.5
other trips pt	0.1	0.0	0.0	0.0	0.0	0.1	1.0
other trips am	2.7	0.5	0.1	1.4	4.3	7.8	2.8
Active Covariates							
Weekend days							
0	26%	34%	50%	58%	53%	48%	46%
1	27%	34%	31%	29%	31%	29%	35%
2	47%	32%	19%	12%	16%	23%	18%
Mean	1.21	0.97	0.70	0.54	0.63	0.75	0.72
WFH hours per week							
1-1	47%	46%	70%	73%	50%	35%	41%
1-5	10%	3%	7%	5%	10%	8%	4%
6-21	22%	16%	18%	16%	24%	26%	22%
22 - 47	21%	35%	4%	7%	15%	32%	34%
Mean	9.87	12.90	3.42	3.85	7.02	12.50	12.51
Working hours per week							
1-18	18%	24%	17%	21%	20%	31%	11%
19 - 25	21%	22%	18%	27%	24%	26%	22%
26 - 29	16%	17%	15%	17%	22%	15%	23%
30 - 33	31%	29%	40%	27%	25%	23%	30%
34 - 46	13%	8%	10%	8%	10%	5%	13%
Mean	34.58	33.03	35.11	33.57	33.77	30.85	35.68
Inactive covariates							
Age							
Mean	46.77	45.97	44.44	47.59	46.65	45.61	42.64
Gender							
Male	48%	50%	60%	54%	51%	34%	54%
Female	52%	50%	40%	46%	49%	66%	46%
Most applicable work situation							
Self-employed entrepreneur	10%	13%	5%	6%	8%	10%	5%
Employed non-governmental job	77%	73%	80%	82%	79%	65%	73%
Employed by the government	14%	14%	15%	13%	13%	25%	22%
Sector							
Healthcare	21%	17%	19%	21%	23%	24%	18%
(Retail) trade	8%	4%	16%	13%	10%	7%	9%
Automation and IT	7%	8%	2%	5%	5%	9%	8%
Education and science	12%	5%	6%	12%	9%	15%	9%
Industry and production	10%	7%	11%	13%	9%	3%	2%
Public administration, security and justice	2%	5%	6%	6%	5%	8%	13%
Financial services	7%	11%	2%	3%	4%	8%	9%
Others	33%	43%	37%	28%	35%	26%	33%
Education level							
Low	13%	20%	22%	21%	10%	12%	12%
Medium	45%	46%	46%	45%	49%	31%	37%
High	42%	34%	32%	34%	41%	56%	51%
Personal income							
<500-1500	6%	13%	17%	13%	6%	10%	9%
1501-2500	29%	32%	30%	34%	28%	37%	24%
2501-3500	40%	33%	36%	27%	43%	28%	36%
>3501	12%	11%	6%	8%	11%	14%	19%
Unknown	13%	11%	12%	18%	12%	11%	11%
Family Cycle							
Single	27%	19%	15%	22%	21%	30%	47%
Adult household	30%	56%	57%	55%	47%	34%	34%
Household with a youngest child with the age ≤ 12	34%	15%	16%	11%	25%	33%	13%
Household with a youngest child with the age of 13 up to 17	9%	10%	12%	11%	7%	3%	6%
Level of urbanization							
Urban, >1500 inhabitants/km^2	51%	60%	54%	61%	53%	65%	78%
Sub-urban, 1000-1500 inhabitants/km^2	18%	11%	13%	15%	17%	10%	11%
Rural, <1000 inhabitants/km^2	31%	29%	32%	24%	30%	24%	11%
Car license							
No	2%	8%	1%	11%	1%	10%	17%
Yes	98%	92%	99%	89%	99%	90%	84%
Car							
0	4%	14%	4%	23%	5%	22%	41%
1	93%	84%	93%	76%	90%	76%	52%
2	3%	2%	3%	1%	4%	1%	1%
4	1%	0%	0%	0%	1%	1%	6%
Mean	1.01	0.88	0.99	0.77	1.01	0.80	0.77

	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Cluster6	Cluster7
Cluster Size	19%	19%	17%	14%	13%	11%	8%
Class label	Car users for many other trips	Low mobility	Car commuters	AM commuters	Car commuters and AM users for other trips	AM users for many other trips	Multi-modal users
Inactive covariates (continued)							
Trips by other modes							
1-1	96%	89%	95%	96%	95%	95%	94%
2-12	4%	11%	5%	4%	5%	5%	6%
Mean (trip rates)	0.19	0.51	0.18	0.14	0.24	0.13	0.18
Distances							
to/from work car (in km)	24.57	0.20	76.60	1.82	78.03	0.20	5.58
to/from work PT (in km)	1.74	0.00	0.27	0.00	0.00	2.21	49.37
to/from work AM (in km)	1.11	0.01	0.30	18.15	0.76	6.75	1.22
to/from work others (in km)	0.67	8.49	3.61	1.66	2.34	1.17	0.78
other trips car (in km)	100.42	20.24	26.99	18.04	20.62	26.94	14.81
other trips PT (in km)	4.15	0.53	0.67	1.47	0.00	3.74	38.86
other trips AM (in km)	6.79	2.64	0.53	5.27	10.47	17.45	6.95
other trips others (in km)	3.19	3.09	1.20	0.74	1.36	2.54	1.06
Total distance (in km)	142.64	35.20	110.17	47.15	113.59	60.99	118.62

Based on the indicator values seven distinct class labels are given: The largest class are **car users for many other trips**, they mostly have trips for other purposes by car. The second largest class represents **low mobility** people, who hardly have any trips. The third class are **car commuters**, these people mostly have commute trips by car. The fourth class are **AM commuters**, similar to the previous class, this class mostly has commute trips, but by active modes. The fifth class are **car commuters and AM users for other trips**. The sixth class are **AM users for many other trips**. Finally, the seventh class are **multi-modal users**, who commute by PT.

Table D.5: Parameters of the 7-class LCA for 2021-2022

Models for Indicators	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Cluster6	Cluster7	Wald	p-value
to/from work car	1.60	-3.83	2.83	-0.23	2.66	-2.81	-0.21	508.07	0.00
to/from work pt	1.31	-2.84	0.49	-2.58	-2.62	1.25	5.00	244.00	0.00
to/from work am	0.53	-4.11	-1.52	3.19	-0.64	2.17	0.38	688.44	0.00
other trips car	1.70	-0.30	0.05	-0.50	-0.03	0.00	-0.93	2338.19	0.00
other trips pt	1.05	-0.91	-0.67	0.11	-3.66	0.56	3.51	216.06	0.00
other trips am	0.57	-1.05	-2.70	-0.11	1.03	1.64	0.62	1097.25	0.00

Intercepts	Overall	Wald	p-value
to/from work car	-1.58	25.97	0.00
to/from work pt	-4.56	46.94	0.00
to/from work am	-1.92	34.38	0.00
other trips car	0.30	62.49	0.00
other trips pt	-3.48	66.24	0.00
other trips am	0.42	48.28	0.00

Model for Clusters	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Cluster6	Cluster7	Wald	p-value
Intercept	-0.583	0.663	-0.460	0.245	0.109	1.327	-1.301	28.341	0.00

Covariates	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Cluster6	Cluster7	Wald	p-value
Weekend days	0.65	0.30	-0.14	-0.41	-0.25	-0.04	-0.10	83.97	0.00
WFH hours per week	0.01	0.04	-0.06	-0.05	-0.01	0.04	0.02	102.30	0.00
Working hours per week	0.01	-0.03	0.04	0.01	0.01	-0.06	0.02	45.52	0.00