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The relations between working from home and travel behaviour: a panel analysis

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Abstract

Policies to increase the amount of time people spend working from home were widely used during the COVID-19 pandemic. Since research suggests that the resulting increase in working from home will outlast these policies themselves, policymakers want to understand the relations between working from home and travel behaviour. We apply longitudinal modelling techniques to estimate the relations between working from home and travel behaviour using panel data from the Netherlands Mobility Panel spanning the years 2017 through 2021. This allows us to separate between-persons and within-persons relations and effects and to see whether these effects changed during the pandemic. We find a negative effect of working from home on commute travel time both before and during the pandemic and a positive effect on leisure travel time only before the pandemic. The sizes of these effects remained roughly similar during the pandemic, although the extent to which working from home affected commute travel time increased during the pandemic. The net effect of working from home on travel time is negative, indicating that working from home policies could be used to reduce travel time. The results also show that some of the relationships between working from home and travel behaviour have changed during the pandemic. As a result, policymakers and transport operators should be careful when estimating future travel demand based on extrapolations of relationships found only before or during the pandemic.

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Introduction

Ongoing developments in information and communication technologies have enabled more people to effectively work from home in the last few decades. This trend is not new, and visions of empty highways because of drastically reduced commuting demand were discussed as early as the 1970 and 1980 s (Kraut 1989; Olson 1983). These visions however did not come to fruition for decades, until the COVID-19 pandemic. In the wake of the COVID-19 pandemic, many governments enforced a work from home mandate in some form (Shibayama et al., 2021). This policy led to, or coincided with, a sharp decline in travel demand (Beck and Hensher 2020a; de Haas et al. 2020a; Molloy et al. 2021).

In many countries, including the Netherlands, the policies intended to reduce the spread of COVID-19 have been scaled down in the spring and summer of 2022. Subsequently, total travel demand increased again. However, the increase in working from home seems to outlast the original measures from the government (Jain et al. 2022), as a substantial share of employees and employers alike have discovered its benefits (Shortall et al. 2021). For policymakers and transport planners, who are interested in a prediction of travel demand in the future, this raises the question what the effects of working from home on travel demand will be in the post-pandemic future. To answer this question, the relationship between working from home and travel behaviour needs to be understood well.

The literature on this relationship shows that people who work from home effectively substitute their travel commute with digital communication technologies, which reduces commuting travel demand. However, it is not clear what effect this has on the time spent travelling for other purposes. Past research has indicated that people who work from home spend more time on non-commute travel, a phenomenon referred to as complementarity (Elldér 2020). In addition, working from home may have the longer-term effect that people decide to accept longer, but less frequent trips, for example by relocating or by changing jobs (Mokhtarian et al. 2004).

However, these general findings do not provide a clear and convincing answer to questions relating to the relationship between working from home and travel behaviour. First, there is no consensus about the relative size of the substitution and the complementary effects: in essence, whether an increase of working from home results in an increase or decrease of total travel demand. In general, earlier studies find a net substitution effect (Mokhtarian et al. 1995), whereas more recent studies find a more balanced or even net complementary effect (Elldér 2020). A possible reason for this discrepancy is the difference in study design. Earlier studies often used relatively small panel samples, based on specific projects or pilots, while more recent studies use larger, cross-sectional travel survey data. The upside of the latter approach is the greater power the larger samples have to generalize findings to the population, but the downside is that the cross-sectional data makes it difficult to disentangle within-person (causal) effects – and the direction of these effects – from between-person (correlational) relationships. This study combines the main benefits of both approaches previously used in the literature: the larger sample size and greater generalizability of the larger cross-sectional studies and the ability of panel data to disentangle within-person from between-person effects. This combination is the first contribution of this study to the literature. To separate the within-person from between-person relationships we use a random intercept cross-lagged panel model (RI-CLPM; Hamaker et al. (2015), which we apply to data from the Netherlands Mobility Panel (MPN), a large panel travel survey.

A second contribution stems from the unprecedented change in working from home behaviour that has been seen since the outbreak of the COVID-19 pandemic. These changes make extrapolating the results from pre-pandemic studies to the post-pandemic world problematic, for two reasons: (1) a new cohort of people started working from home during the pandemic and (2) people worked many more hours from home during the pandemic than they did before the pandemic. Studies that only collect data during the pandemic can be of help, but they too can not fully solve this problem as the behaviour during this period is inevitably intertwined with the broader effects of the pandemic. To connect the pre-pandemic and post-pandemic studies then, the solution is to analyse the behaviour during both tracts of time. Doing so is the second contribution of this paper to the literature, as we use data collected both before and during the COVID-19 pandemic. We apply the RI-CLPM to data collected between 2017 and 2021. This effectively gives us two wave-pairs collected fully before the pandemic (2017 to 2018 and 2018 to 2019) and two wave-pairs collected partly during the pandemic (2019 to 2020 and 2020 to 2021), which allows us to test whether the pandemic resulted in a change to these within-persons relations.

The insights of this study help provide policymakers, road authorities, and public transport operators with better predictions for the effects of working from home on travel behaviour. These predictions affect both relatively short-term decisions, such as public transport operational schedules, as well as longer-term decisions, such as road infrastructure investments. More insights into the relations between working from home and travel behaviour thus are necessary both during the more short-term transition out of the pandemic into the post-pandemic 'normal' and the long-term predictions of how working from home will shape travel demand in the more distant future. Furthermore, it may help policymakers and employers in evaluating the effects policies related to working from home on travel behaviour.

In Sect. 2, an overview of the literature on working from home and travel behaviour is provided, culminating in a conceptual model. In Sect. 3, the methods and data are introduced and described. Section 4 contains the results from the estimated model, and the conclusion and discussion can be found in Sect. 5.

Literature overview

This section contains an overview of the literature on the relations between working from home and travel behaviour. First, an overview of different conceptual relations between working from home and travel behaviour is shown, followed by a more in-depth look at these identified relations. Then we summarise the literature on the effects of COVID-19 on working from home and travel behaviour.

Conceptualising the relationship between working from home and travel behaviour

The relationship between working from home and travel behaviour has been studied since at least the early 1970s, when Nilles (1976) proposed it as a solution to reduce commute travel in the face of the oil crisis (He and Hu 2015). With the rapid increase in information and communication technologies, working from home has become a more feasible solution for a greater part of the population in the decades since (Harpaz 2002; Siha and Monroe 2006).

Despite seeing an (albeit relatively small) increase in working from home in developed nations in the decades between the 1970s and 2019, total time spent travelling remained relatively constant during the same time as well (Kasraian et al. 2018; Susilo and Maat 2007). It appears thus that until the COVID-19 pandemic, the effect of working from home on travel behaviour was relatively small, at least for the population as a whole.

This small or non-existing effect can partly be explained by the relatively low rate of adoption of working from home, but also partly by the complex relationship between working from home and travel behaviour. For one, the literature suggests that there is a bi-directional relationship between working from home and travel behaviour (Mokhtarian et al. 2004). Part of this relationship is due to self-selection effects, as people who choose to work from home, and thus have the option to do so, have different travel behaviour habits than people who do not choose to do so (He and Hu 2015). Another part is due to a relationship between commute distance and working from home, where people with a longer commute distance seemingly choose to work from home more often (de Vos et al. 2018; Zhu 2012). These issues make it impossible to estimate the unbiased effects of working from home on travel behaviour without controlling for endogeneity (He and Hu 2015). One of the best ways of doing so is using panel studies, which however are rare in the literature. One application of a panel by de Vos et al. (2018) uses a fixed-effects model to account for time-invariant confounders to separate within- and between-person effects. They find that people who work from home are willing to accept a 5% longer commute. This effect size is smaller than the 11.7% longer commute they found using an OLS model which does not account for time-invariant confounders.

Further complicating the matter is the fact that the effect of working from home on travel behaviour is not as straightforward as it may seem at first glance (Mokhtarian 1990; Salomon 1986; Zhu 2012). Certainly, by replacing a physical (travel) commute with a digital telecommute, working from home causes people to make fewer commute travel trips. This effect is referred to as the substitution effect, where the use of ICT substitutes for physical travel (Andreev et al. 2010). However, the lack of a physical commute saves time, which can be used for travelling for other purposes (Elldér 2020). If this is the case, working from home also generates new trips, an effect referred to as complementarity (Andreev et al. 2010).

A theoretical explanation for this complementary effect can be found in the theory of constant travel time budgets (Ahmed and Stopher 2014; Milakis and van Wee 2018), which states that people like to spend, on average, roughly the same amount of time (per day) for travelling. On a societal level, the existence of constant travel time budgets would mean that people balance travel time spent on commuting and travel time spent on leisure[1]. If the theory turns out to be true, then if one goes down, the other will go up. In other words, reduced commute travel resulting from working from home will result in a rebound effect (Caldarola and Sorrell 2022; Hostettler Macias et al. 2022; Rietveld 2011). These rebound effects might result from the within-person complementary generation of leisure travel described above as the complementary effect, but also from between-person effects. Examples of potential mechanisms are reduced crowding and congestion leading to induced demand, greater availability of household cars to other people in the household, and longer-term decisions

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[1] We use a broad definition of leisure travel, encompassing all trips made for non-work and non-education related purposes. Stricter definitions of leisure travel also exclude habitual trips made for maintaining one's lifestyle, such as groceries. We do include these trips in our definition of leisure travel.
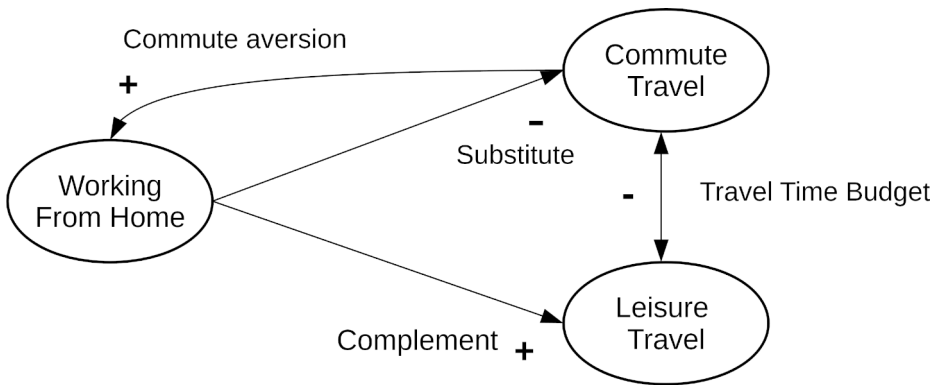
Fig. 1 The conceptual model of this study

regarding the distance between the workplace and the residence (Rietveld 2011; Wöhner 2022).

The relationships discussed in this section are graphically summarized in the conceptual model for this study, which is given in Fig. 1. We discussed that there are two distinct effects of working from home on travel behaviour: a negative effect on commute travel, referred to as substitution, and a positive effect on leisure travel, referred to as complementarity. One possible mechanism behind these substitution and complementary effects is that of a constant travel time budget, which should then also be observed for other reasons that are not related to working from home.

It is important to point out here that the above conceptual model is an overview of the relationships between working from home and travel behaviour that are expected to exist, based on the overview of the literature. As will be clarified later in the discussion of the research method and the operational model, we empirically test all possible relationships between the concepts in this conceptual model. The conceptual model thus serves as a theoretically underpinned base for further analyses in this study – both how they are set up and how they are interpreted.

The effects of working from home on travel behaviour

In this subsection, we will provide an overview of the literature discussing the various relationships visualized in Fig. 1. We will start by looking at the effects of working from home on travel behaviour, and whether there is a net substitution or complementary effect. We will then dive into the literature on travel time budgets.

Net substitution or net complementarity?

The complex conceptual relations between working from home and travel behaviour make it difficult to adequately assess the relative size of the effects that working from home has on travel behaviour. Earlier review studies show that in total, working from home reduces travel demand and thus that the substitution effect is stronger than the complementary effect (Andreev et al. 2010; Mokhtarian 1991).

Several more recent studies indicate that people who work from home travel either a greater total distance or make more trips than people who do not work from home (de Abreu e Silva and Melo 2018; He and Hu 2015; Zhu 2012; Zhu et al. 2018). Elldér (2020) found that people who work a full day from home travel a smaller distance, but that people who work from home for part of the day travel more often and for longer distances. (Caldarola and Sorrell 2022) found a similar effect: working from home is associated with greater distances travelled up to a certain point (working from home 3 or more days a week), where they travel less. Wöhner (2022) finds that people who telework travel a similar distance as people who do not. All the above studies find that working from home is related to making fewer commute trips, but more non-commute trips. Summarising then, many recent studies find that people who work from home travel more than people who do not, suggesting that the complementary effect is at least similar in size to the substitution effect.

Between-persons vs. within-persons effects

This raises the question why there is such a difference between the general findings of the earlier and later studies: research design or a real underlying change in the effects over time. There is a striking difference in research design between many earlier and many later studies. Earlier studies typically used data collected from smaller sample sizes, collected specifically around one or multiple projects where people increased the amount of time they would work from home. Later studies more often use data from general travel surveys, generally consisting of larger sets of respondents that are meant to be representative of a region or country (Elldér 2020). Earlier studies often collected longitudinal data (from before and after people started working from home), whereas later studies used cross-sectional data. These later studies then cannot disentangle between-persons from within-persons effects. Another drawback of using general travel surveys is that the measurement of working from home is often not so precise: respondents for example indicate that they work from home 'regularly' or 'sometimes'. Elldér (2020) showed that using more precise measurements, such as when people telework and for how many hours, leads to different results with stronger substitution effects. They posit that more recent studies typically use less precise measurements of working from home, which is one explanation for the difference in results between earlier and more recent studies.

The disruption of the COVID-19 pandemic

The COVID-19 pandemic has had a profound impact both on working from home and travel behaviour. This impact is the result of two related effects: the fear of the pandemic causes people to travel less often, and government mandates aiming to curb the spread of the virus have severely affected people's ability to employ activities outside of their homes.

Effects on working from home

Research shows that the amount of time people worked from home increased during the COVID-19 pandemic in many countries, all over the world (Beck and Hensher 2020a; de Haas et al. 2020a; Downey et al. 2021; Kolarova et al. 2021; Rafiq et al. 2022; Yilmazkuday 2020; Zhang et al. 2021a, b). This is the result of policies by many national governments,

which aimed to inhibit the transmission of the virus by reducing contacts between people both at work and whilst travelling to work. This sudden development contrasts the gradual growth of working from home over the past decades (Mokhtarian 2020; Stiles and Smart 2021). Many people started working from home during the pandemic and discovered its benefits and drawbacks for the first time (Reiffer et al. 2022). This means that people were generally not able to self-select into work circumstances that allowed them to work from home, but rather were either forced to do so or suddenly found themselves able to (Ecke et al. 2022). The effects of working from home for these new groups of people can be vastly different to those found before the pandemic, which is based on a much narrower group (Kramer and Kramer 2020; Reiffer et al. 2022). Finally, studies find that a substantial number of people that started working from home have been content with this change in their life and expect to work from home post-pandemic as well (Jain et al. 2022; Shortall et al. 2021). This means that increased levels of working from home will have a lasting impact on working from home, even after the pandemic and the associated measurements are no longer a driving force behind working from home adoption.

Effects on travel behaviour

Simultaneously, activity-travel patterns changed drastically during the pandemic as well. In general, commuting travel decreased (Beck et al. 2020; Beck and Hensher 2020b; de Haas et al. 2020a; Shamshiripour et al. 2020). This decline was most substantial for public transport use (Beck et al. 2020; de Haas et al. 2020a), which can at least partly be explained by the increase in working from home. Studies indicate that working from home has a relatively strong negative effect on public transport use (Bohman et al. 2021; Currie et al. 2022; Downey et al. 2022; Sweet and Scott 2022), due to the finding that former public transport commuters are commonly able to work from home. Some studies also report a shift towards travel for leisure purposes, especially those made on foot or a bicycle (Campisi et al. 2022; Christidis et al. 2022; de Haas et al. 2020a; Zhang et al. 2021a, b). These changes can only partially be explained by the increase in working from home: other contact-reducing measures (up to and including lockdowns) and the general fear of being infected with the disease of course played a much larger role as well.

Research methods

This section describes the data and methods used to investigate the relations visualized in the conceptual model. The data panel is described first, followed by the operationalisation of the concepts into variables. Then descriptive statistics of the data are presented, followed by a description of the research method. Finally, the section culminates in the specification of the final model, descriptions of model estimation and an operational model.

Data & sampling

To investigate the relationship between working from home and travel behaviour, we use data from the MPN, a longitudinal household panel that consists of a 3-day travel diary and a set of questionnaires (Hoogendoorn-Lanser et al. 2015). Respondents for the MPN

are recruited from an invite-only internet access panel (IAP), the Kantar NIPObase panel. Respondents for this larger IAP are recruited using register data, and it is not possible to sign-up to become a member of this IAP. Members from this larger IAP are recruited to participate in the MPN based on their socio-demographic characteristics, which ensures that the MPN itself tracks the population distribution on these variables. For example, if younger people are underrepresented in the MPN, then in the next wave more young people are invited from the larger IAP. Between 30% and 50% of respondents accept this initial invitation to participate in the panel. Response rates for the respondents within the panel vary between 85 and 90% for each yearly wave.

We use five waves of data from the MPN, spanning the years 2017 through 2021. Effectively, this gives us three waves of data collected before the COVID-19 pandemic and two waves collected during the COVID-19 pandemic. Each wave is collected in the Fall of each year. During the pandemic years of 2020 and 2021, COVID-19 the government recommended that people work from home when able. Furthermore, COVID-19 cases were rising during both years as we transitioned from relatively carefree summers to winters with prolonged lockdowns. In 2020, stricter measures were introduced during the fieldwork period. In 2021 measures were slightly relaxed halfway through, but the increase in measures culminating in a lockdown only started after the fieldwork period was over. The timing of the MPN measurements is visualized together with the COVID-19 hospital admissions and the Oxford CGRT Stringency Index(Hale et al. 2021) in Fig. 2.

Since we are interested in the relationship between work and travel behaviour in this study, we only use MPN respondents that worked at least 16 h per week during each wave. Furthermore, we use a pure-stayer sample of respondents who fully participated in all five waves. The use of a pure-stayer sample allows us to more directly compare the effect sizes found before and during the pandemic, as they are based on data generated by the same people. The final pure-stayer sample consists of 1100 respondents. A possible drawback of using a pure-stayer sample is the potential of non-random dropout, which could lead to a skewed data set. To test whether this is the case, we give a distribution of socio-demographic characteristics for both the pure-stayer sample and the cross-sectional sample of the 2019 MPN wave in Table 1. These can be compared to their distribution in the population, which are based on data registers produced in cooperation with Statistics Netherlands by the Dutch Marketing, Research, and Analytics organization (MOA Expertise Center 2023).
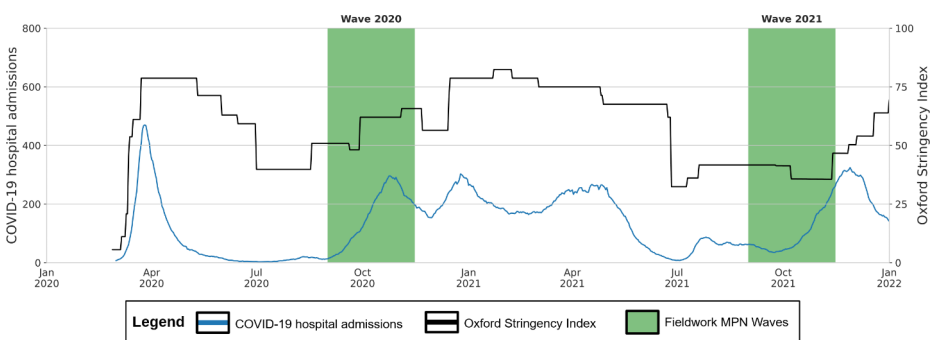
Fig. 2 Fieldwork period for the MPN waves visualized with COVID-19 hospital admissions and Oxford Stringency Index

Table 1 Sample distribution of the pure-stayer sample, the cross-sectional participants of the 2019 wave, and the population

		Study Sample (pure stayer)	Cross-sectional Sample (2019 wave)	Population (18+years old with gainful employment)
Gender	Male	52	50	54
	Female	48	50	46
Age (Years)	18–29	8	15	17
	30–39	31	27	23
	40–49	25	26	25
	50–59	27	24	25
	60+	9	8	9
Education	Low	11	14	14
	Medium	38	40	43
	High	52	46	43
Net Personal Income (€/ month)	Low (< €2000)	32	38	45
	Modal (€2000 to €3000)	46	43	35
	High (> €3000)	22	19	20
Urban Density (addresses/m²)	<500	7	9	Not available
	500–1000	20	21	
	1000–1500	17	18	
	1500–2500	33	32	
	>2500	23	20	
Household type	Single	26	20	Not available
	Adult household	39	44	
	Kids<13	29	28	
	Kids>13	7	8	

This comparison between the socio-demographics of the pure-stayer sample and the cross-sectional sample, given in Table 1, shows that drop-out is indeed higher in some subgroups, leading to a slightly skewed sample. In particular, younger people (younger than 29 years) seem to drop out more often. This leads to an underrepresentation of this group in our final sample compared to the population. Both the cross-sectional and the pure-stayer sample also contain a slight overrepresentation of higher-educated, higher-income groups.

Operationalisation

The main interest of this research is to (a) determine the direction and size of the (causal) relations between working from home and travel behaviour and (b) find whether these effects changed during the COVID pandemic. To find the bidirectional (causal) relations between working from home and travel demand we need to include four variables within each wave.

First, we include the weekly number of hours worked from home and the weekly number of hours worked in total. These two variables allow us to capture the effect of working more from home, whilst controlling for the effects of simply working more. Effectively, we

need to separate increases in working from home that result from a simple increase in the total number of hours worked and increases that result from a shift from hours worked in a separate work location (for example an office) to hours worked from home. These variables are measured using a questionnaire, where respondents are prompted to answer how many hours on average they worked in total in the last few weeks. Afterwards, they distribute these hours over the location where they worked, giving us the weekly number of hours spent working from home. This information is recorded for a general week during the field-work period, but respondents do not specify on which specific days they worked from home.

For travel behaviour, we distinguish two types of travel. The first is commute travel, which we define as travel to move to and from the work location. Second, we distinguish leisure travel, which we broadly define as all travel that is not made specifically either for work (=either commuting or business travel) or educational purposes. We operationalise travel behaviour as the time spent travelling for either commuting or leisure purposes during the 3-day observational period of the MPN. We choose to use travel time, as opposed to travel distance, since we assume that people base their decisions on changes in travel time. In other words, we expect that the time saved by commuting less because of working from home is the most tangible benefit felt by people who work from home and that it is this saved up time they might spend on travelling for other purposes. This is also the main thought behind the theory of constant travel time budgets, which we can tie into our research in this way.

We extend the model beyond these four variables in two ways. First, we include the number of weekend days that are included in a respondent's travel diary allotment. MPN respondents keep 3-day travel diaries, where the allotted weekdays are kept stable across waves. Some respondents then have 1 or 2 weekend days in these allotted days, whereas others have none. We need to control for these differences to get more accurate between-person relations. Second, we want to allow for some form of heterogeneity concerning travel modes in the model. This adds information that is highly relevant to policymakers, road operators, and transit planners. To do so, we add the most often used commute mode in the last pre-pandemic wave (2019). This allows us to attain information on the extent to which commute demand for the various modes has been affected by working from home because of the pandemic. The commute mode is operationalised using two dummy variables: people who commuted by public transport and people who commuted by car. The reference group then consists of all people who commuted by other travel modes.

Data description

In this section, we describe and inspect the data. Means, medians, standard deviations and serial correlations for the four time-variant variables are given in Table 2.

All variables' mean, median and standard deviation values are stable across the three pre-pandemic years. This stability disappears when comparing both 2020 and 2021 to the years before the pandemic, especially for the number of hours worked from home and commute time travelled. The average number of hours worked from home substantially increased in the year 2019/2020, before levelling off at an average of 10 h worked per week in 2021. Both commute and leisure travel time decreased: from 74 min to 3 days for commute travel in 2019 to 40 min in 2020 and from 122 min to 3 days for leisure travel to 104 min. The decrease in commute travel time thus was much more substantial than the decrease in leisure travel time.

Table 2 Means, medians, standard deviations and serial correlations for the time-variant variables

		2017	2018	2019	2020	2021
Hours worked (hours/week)	Mean	35	35	35	35	35
	Median	36	36	36	36	36
	SD	8.9	8.6	8.5	8.4	8.0
	Serial correlation[1]	-	0.81	0.85	0.81	0.85
h WFH (hours/week)	Mean	3	3	3	12	10
	Median	0	0	0	4	3
	SD	6.3	6.8	6.5	15	13
	Serial correlation[1]	-	0.66	0.75	0.40	0.77
Commute travel time (hours / 3 days)	Mean	1.30	1.27	1.23	0.67	1.30
	Median	1.00	0.92	0.80	0.17	1.00
	SD	1.43	1.43	1.47	1.07	1.43
	Serial correlation[1]	-	0.50	0.58	0.29	0.41
Leisure travel time (hours /3 days)	Mean	1.98	2.15	2.03	1.73	1.98
	Median	1.45	1.62	1.57	1.20	1.45
	SD	1.95	2.12	1.95	1.90	1.95
	Serial correlation[1]	-	0.36	0.35	0.35	0.44

1: Year-on-year serial correlation. That is, the correlation within one variable of the given year with the previous year

Table 3 Correlations between time-variant variables

	Hours worked	Hours WFH	Commute travel time	Leisure travel time
Hours worked	1	*0.31*	*0.13*	*-0.041*
h WFH	**0.26**	1	*-0.24*	*0.040*
Commute travel time	**0.20**	**-0.068**	1	*-0.11*
Leisure travel time	**-0.035**	**0.057**	**-0.18**	1

Bivariate correlations in the lower left (**bold**) are from the pooled 2017–2019 data; correlations in the upper right (*italic*) are from the pooled 2020–2021 data

Another way of showing the stability of the variables over time is by looking at the serial correlation of each variable. The serial correlation refers to the correlation between the measurements at timepoint t and the measurements at the previous timepoint t-1. These correlations are relatively stable for the number of hours worked in total and leisure travel time throughout the sampling period. However, there is a very strong decrease in the serial correlation between 2019 and 2020 for the number of hours worked from home and commute travel time compared to the serial correlation before the COVID-19 pandemic. This shows that the COVID-19 pandemic disrupted both the hours worked from home and commute travel time, but not the total hours worked and leisure travel time.

Finally, we can get a first appreciation for the relations between the variables by studying the bi-variate correlations between the time-variant variables for both the years before and the years during the COVID-19 pandemic, which are given in Table 3.

As expected, based on the conceptual model, the correlation between working from home and commute travel is negative both before and during the COVID-19 pandemic. The magnitude of the correlation is much larger during the pandemic than it was before the pan-

demic. The correlation of hours worked from home and leisure travel time is small, but positive – again in line with the expectation set out in the conceptual model – and did not change in magnitude nearly as much. The correlations between commute and leisure travel time are negative, and the correlations between working and working from home are positive.

Method and model specification

To determine the longitudinal relations between the variables, we use a random-intercept cross-lagged panel model (RI-CLPM), which is an extension of the cross-lagged panel model (CLPM; (Finkel 2011). The CLPM is an often-used model to study panel data used to empirically test the bidirectional effects between multiple concepts that are measured over time. To do so, the CLPM specifies auto-regressive relationships, which are supposed to control for the stability of a variable over time. The cross-lagged relationships between the constructs are then supposed to represent the causal processes between the variables. As pointed out by Hamaker et al. (2015), this approach assumes that the score of each variable for every person varies over time around the same sample mean. This assumption is problematic, as most variables do contain stable differences between individuals. For example, some individuals will persistently work more hours per week than others across all measurements, which is ignored by the CLPM.

Hamaker et al. (2015) therefore argue that researchers should not only control for temporal stability across the sample, but also for the time-invariant stability of each variable on the level of the individual. Doing so effectively separates within-person effects over time from constant between-person differences. This is achieved by including random intercepts, which account for the trait-like, time-invariant stability of the variables. The random intercepts thus capture the between-persons differences, allowing the (auto)-regressive structure to specifically capture within-person effects. The resulting auto-regressive coefficients can then be interpreted as within-individual carry-over effects (Mulder and Hamaker 2020), meaning that a positive effect indicates that a higher (or lower) than expected score is likely to also have a higher (or lower) than expected score during the next observation, where the expected score is based on the average, trait-like, score per respondent. Similarly, the cross-lagged effects represent that an individual with a higher-than-expected score on one variable also has a higher-than-expected score on the other variable in the next measurement. These effects are directional and since they represent within-individual changes, they can be more correctly assumed to represent causal processes on the within-individual level than parameter estimates from CLPMs. The RI-CLPM also allows us to estimate the correlations between the random intercepts, which can be interpreted as the general between-person relations between the concepts associated with each of the random intercepts in question (Mulder and Hamaker 2020).

The main methodological challenge in this study is that we need to account for the disruption caused by the COVID-19 pandemic, which can be termed a 'regime change' and threatens the ability to draw causal inferences from the model (Zyphur et al. 2019). We must find a solution for the resulting disruption to the stable, trait-like differences between individuals. Earlier we saw in Table 2 that the serial correlations for working from home and commute travel time were much lower between the years 2019 and 2020 than they were before the pandemic. This provides a challenge, as the random intercepts in a RI-CLPM typically assume that there are stable differences between individuals across the duration of

the study by fixing all factor loadings of the random intercept to one (Hamaker et al. 2015). The pandemic makes this a problematic assumption, especially for working from home and commute travel time. A potential solution is to remove the constraint on the factor loadings for the measurements during the COVID-19 pandemic (Hamaker et al. 2015; Zyphur et al. 2019) and to let the model estimate factor loadings separately for both measurements. We test this specification against the typical specification with fixed factor loadings to determine which provides the best fit to the data.

Furthermore, we are interested in answering the question whether this regime change resulted in changes to the within-person effects during the COVID-19 pandemic compared to before the pandemic. We can do so by estimating a model where the lagged parameters are constrained to be the same over the whole duration over time and testing it against a model where we relax this constraint. We will thus test a model with only one set of parameters for the entire duration of the study against a model with two sets of parameters, one for the lagged effects before the pandemic (2017 -> 2018 -> 2019) and one for the lagged effects during the pandemic (2019->2020->2021). Again, we can test which model best fits the data. If the latter model fits best, then we can say that the within-person relations changed during the pandemic.

Finally, we add two extensions to the model discussed by Mulder and Hamaker (2020), both relating to the incorporation of time-invariant predictors of the time-variant variables. Time-invariant variables are stable over time, and in this model specification we expect them to have affected the time-variant variables. The first extension is the use of the number of weekend days as a predictor of the random intercepts. Effectively, this controls the trait-like stability of the variables for the differences in our measuring instrument that assigns a different number of weekend days to the respondents. Second, we regress the time-variant variables for the waves during the pandemic on the commuting mode used in the last wave before the pandemic. This gives us additional insight into the effects of working from home on the use of different travel modes.

Model estimation

In this section, we first compare the model fit of several models introduced above to see which model provides the best fit to the data. As introduced in Sect. 3.4 above, we estimate five different models:

1) A RI-CLPM with equality-constrained lagged parameters where the variance and covariance of the random intercepts are constrained to zero. This effectively is a CLPM.
2) As in 1, but without the constraints on the variance and covariance of the random intercepts.
3) Removing the equality constraints on the lagged parameters, instead estimating two sets of parameters. One before the pandemic, and one during the pandemic.
4) Removing the constraints on the factor loadings of the 2020 and 2021 measurements of working from home and commute travel time.
5) Removing the constraints on the factor loadings of the 2020 and 2021 measurements of all four variables.

All models are estimated using the R-package Lavaan (Rosseel 2012). The goodness-of-fit statistics, as given by Hooper et al. (2008), are displayed in Table 4.

The CLPM fits relatively poorly to the data with a chi-square value of 1339 (df=192, p=0.000) and unsatisfactory RMSEA, SRMR, and CFI scores. The RI-CLPM (model 2) provides a much better fit to the data based on these criteria. The equality constraint on the lagged parameters is relaxed in the step to model 3. This relaxation again results in a large increase in model fit and is to be preferred based on all goodness-of-fit indicators. For model 4, the factor loadings of the random intercepts pertaining to the COVID-19-influenced measurements of working from home and commute travel time are no longer constrained. This again results in a relatively large increase in model fit, with a very good model fit as indicated by the CFI (0.977), RMSEA (0.039), and SRMR (0.038). The final step to model 5, where the factor loadings of all measurements during the pandemic were no longer constrained proves to be less effective. Model 5 is not to be preferred over model 4 based on the Chi-square difference test and the AIC and BIC values. A simplified schematic overview of the variables and relationships of the final model is given in Appendix A.

Results & discussion

This section describes and interprets the empirical results from the estimated model fitted to panel data in the Netherlands. The section is structured around the expected relations from the conceptual model given in Sect. 2. First, the results relating to the effects of working from home on both commute and leisure travel time are interpreted. Then, the effects of travel time on working from home and the relations between the two travel time variables are discussed. Finally, we discuss the stability of the variables and take a brief look at the effect of commuting by different modes.

As described in Sect. 3, the RI-CLPM estimates two different effects: the within-person directional effects, which vary over time, and the between-person correlations, which do not vary over time. Both sets can be analysed together to attain a comprehensive overview of the relationships between working from home and travel behaviour.

Table 4 Goodness-of-fit statistics for the five structural equation models

Model	Model 1	Model 2	Model 3	Model 4	Model 5
Description	CLPM; Equality constraint	RI-CLPM; Equality constraint	RI-CLPM; Two sets of parameters	RI-CLPM; 2 RI Factor loadings relaxed	RI-CLPM; All RI factor loadings relaxed
Degrees of freedom	192	182	166	162	158
Df difference	-	10	16	4	4
Chi-square	1339	653	487	428	423
Chi-square difference (test)	-	686 (p<0.001)	166 (p<0.001)	60 (p<0.001)	4.8 (p=0.308)
CFI	0.902	0.960	0.973	0.977	0.977
RMSEA	0.074	0.049	0.042	0.039	0.039
SRMR	0.077	0.068	0.056	0.038	0.037
AIC	109,113	107,958	107,824	107,772	107,775
BIC	108,624	108,497	108,443	108,411	108,434

The effects of working from home on travel time

The relationship between working from home and travel time is interpreted using both the within-person and between-person coefficients estimated in the RI-CLPM. First, we will look at the within-person estimates. The unstandardized within-individual effects between the four time-variant variables, as well as the effect of the time-invariant predictor, are given in Table 5. As explained in Sect. 3.4, the auto-regressive coefficients can be interpreted as within-individual carry-over effects and the cross-lagged coefficients represent that an individual with a higher-than-expected score on one variable also has a higher-than-expected score on the other variable in the next measurement.

We find negative unstandardized effects from working from home on the travelled commute time both before the pandemic (-0.022) and during the pandemic (-0.023). This effect did not change during the pandemic compared to before the pandemic. We find a positive unstandardized effect of working from home on leisure travel time before the pandemic (0.013), which however nearly disappeared during the pandemic. These estimates provide evidence for the existence of both substitution and complementary effects. The latter effect however is only found to be statistically significant before the pandemic. Both before and during the pandemic we can conclude that the substitution effect appears to be stronger than the compensatory effect.

However, it is important to realize that standardized estimates can still change drastically, even if the unstandardized estimates are relatively stable. The standardized estimates of the

Table 5 Unstandardized within-individual effects between time-variant variables

Independent variables	Dependent variables							
	Effects before COVID-19 pandemic (2017–2019)				Effects during COVID-19 pandemic (2019–2021)			
	Work hours	WFH hours	Commute time travelled	Leisure time travelled	Work hours	WFH hours	Commute time travelled	Leisure time travelled
Time-variant variables								
Work hours	0.407***	-0.062**	0.003	-0.019**	0.241***	-0.111	0.008	-0.010
WFH hours	0.019	0.645***	-0.022***	0.013*	-0.008	0.403***	-0.023***	0.004
Commute time travelled	-0.033	-0.327***	0.212***	0.044	-0.197*	-1.615***	0.159***	0.106**
Leisure time travelled	-0.019	-0.109*	0.029*	0.063**	-0.171**	-0.492***	0.020	0.104***
Time-invariant predictors								
Public Transport Commuter[a]					0.855*	8.458***	-0.165	-0.075
Car Commuter[a]					0.352	-0.551	0.067	-0.081

In this and following tables, ***p<0.01, **p<0.05, and *p<0.1

a. reference: all other travel modes as main commute mode

model are given in Appendix B. This is the case if the distribution of the variables changes over time. We saw in Sect. 3.3 that the standard deviation for working from home increased during the COVID-19 pandemic, whereas the standard deviation for commute travel time decreased. Since we saw that the unstandardized parameter remained nearly constant, we can conclude that the standardized parameter estimates of the effect of working from home on travel time increased during the COVID-19 pandemic. It increases from -0.110 (2018 to 2019) to -0.132 (2019 to 2020), to -0.249 (2020 to 2021). So even though the unstandardized effect barely changed at all during the same period, the variation in working from home had a larger influence on the variation in commute travel time during the pandemic than it did before the pandemic. In other words, changes in working from home were a greater driver of changes in commuting travel time during the pandemic than before the pandemic.

The above interpretation of the within-person effects can be complemented by an analysis of the between-person relations, which are estimated by the RI-CLPM as the correlations between the random intercepts. These correlations represent the time-invariant relations between the variables across the respondents. Table 6 contains the correlation coefficients between the four random intercepts.

The positive correlation (0.403) between the number of hours worked and the number of hours worked at home for example indicates that people who work more hours also work more hours from home. Similarly, people who work more also tend to commute more (correlation = 0.432). So far, these findings are not very surprising.

However, that changes when we turn our attention to the relations between working from home and travel time. We see a relatively strong and significant correlation between the number of hours worked from home and commute travel time (0.180). This finding contrasts the negative within-person effects of working from home on commute travel time discussed above. This means that people who work more hours from home in general travel more time for commuting. However, variations within the individual have an effect in the opposite direction: a higher-than-expected score for working from home results in a lower-than-expected score for commute travel time in the next measurement. Similarly, we also note the fairly large and positive correlation between working from home and leisure travel time (0.183), which stands in contrast with the fairly small within-person effect of working from home on leisure travel time, which was even insignificant during the COVID-19 pandemic.

The key takeaway then is that the within-persons and between-persons relations between travel time and working from home differ from one another. This implies that research methods which are unable to separate within-persons from between-persons effects will, to varying extents, overestimate the size of the complementary effect and underestimate the size of the substitution effect. This would explain the difference between the more recent findings, based on cross-sectional studies, that working from home will lead to an increase in travel and the less recent findings, based on panel studies, that working from home leads to a decrease in travel, as discussed early in Elldér (2020). This explanation complements

Table 6 Correlations between the random intercepts

	Hours worked at home	Commute travel time	Leisure travel time
Hours worked	0.403***	0.432***	-0.062
h worked at home		0.180**	0.183***
Commute travel time	-		-0.141**

the finding in Elldér (2020) itself, where the author poses that the difference in measurement of working from home between earlier and later studies explains the difference in outcomes. Both results together suggest that future researchers studying the effects of working from home on travel demand should both use more direct measurements of working from home and ideally use methods that can separate between-person from within-person differences.

Travel time budgets and effects on work and work from home

Based on the theory of constant travel time budgets, we expected a negative relationship between commute and leisure travel time. However, the model estimates either insignificant or positive within-person effects between these two variables. One explanation might be that as people move through life, they go through life events that increase mobility in general. Furthermore, the effect during the pandemic likely reflects a temporary unwillingness to travel due to underlying concerns about the virus. Turning our attention to the between-person correlations between the two travel time variables, however, we do find a negative relationship between commute and leisure travel time. This means that people who spend more time travelling for leisure purposes, in general, spend less time commuting. Again, the within-persons and between-persons effects seem to differ markedly. These findings would suggest that the theory of constant travel time budgets works on the between-person level, but not necessarily on the within-person level. Reduced commute travel (either due to increases in working from home or not) thus could lead to other people travelling more, but not necessarily to increases in leisure travel within the individual. This is a useful finding to keep in mind, as it seems to indicate that rebound effects (Caldarola and Sorrell 2022; Hostettler Macias et al. 2022; Rietveld 2011) at least partly occur between-persons. For the effectiveness of working-from-home policies, this would indicate that some of the reduced travel demand resulting from the net substitution effect within the individual, as discussed above, will be offset by increased travel demand from other persons.

We also find some effects of commute and leisure travel time on working from home. We find sizeable negative within-persons effects from commute time on working from home (-0.327 before the pandemic, -1.615 during). As explained in Sect. 2, we initially expected a positive effect here, as people with longer commutes net a larger gain by working from home more often. However, we operationalised commute travel time as the total amount of time travelled for commuting purposes, which does not necessarily encompass the amount of time travelled per commute. During the pandemic, we also find significant negative within-person effects of both commute and leisure travel time on working hours. This suggests that people that start to travel less, will then work fewer hours in the following year. There is no clear theoretical explanation for these findings. Perhaps the model is picking up certain life events that more frequently occurred during the pandemic, which results in changes to both the travel- and work-related variables.

Stability & mode heterogeneity

The sizes of the auto-regressive parameters also differ between the estimates before and during the pandemic. For all variables, these parameters were smaller during the pandemic than they were before the pandemic. This indicates a smaller carry-over effect from one measurement to the next of the behaviour seen, which indicates less stable behaviour. This

makes sense, as we concluded earlier that the COVID-19 pandemic resulted in changes to both work- and travel behaviour.

Finally, we also included the main commuting mode as recorded during the last measurement before the pandemic (September 2019) as a time-invariant predictor of the variables in the following waves during the COVID-19 pandemic. Public transport commuters differed statistically from all other commuters in terms of the number of hours they work from home. People whose most often used commuting mode before the pandemic was public transport were far more likely to work from home during the pandemic (roughly 8,5 h more per week compared to the reference group, which was non-car, non-public transport commuters). This confirms earlier findings that the shift to working from home was especially large for public transport commuters (Bohman et al. 2021; Currie et al. 2021; Downey et al. 2022).

Conclusion

In this study, we set out to 1) separate the within-person from between-person relations between working from home and travel behaviour using panel data and b) find whether the within-person relations changed during the COVID-19 pandemic. To do so, we estimated a random-intercept cross-lagged panel model using panel data collected both before and during the pandemic.

The results show that people who increase the amount of time they spent working from home reduce their commute travel. We also find a smaller, positive effect of working from home on leisure travel time before the COVID-19 pandemic, although it is only statistically significant if we accept a 10% threshold. Both before and during the pandemic, the within-person negative effect of working from home on commuting travel time is greater than the positive effect on leisure travel time. The net effect of working from home on the amount of time people spent travelling thus seems to be negative both before and during the pandemic. This finding contradicts most of the more recent literature on the effects of working from home on travel behaviour, where people who work from home are generally found to travel more than people who do not (Caldarola and Sorrell 2022; Wöhner 2022). We do find positive between-person relations between working from home and both commute and leisure travel time. We postulate therefore that the difference between these findings at least partly result from our panel design, and that separating the within-person and between-person relations offers new insights into the relations between working from home and travel behaviour.

Turning our attention to the differences in the relations between working from home and travel behaviour before and during the pandemic, we see that the effect of an additional hour worked from home on commute travel time was relatively stable. However, the extent to which commute travel time is determined by working from home sharply rose during the pandemic. This is the result of both a smaller variance in commute travel time and a larger variance in working from home. The extent to which working from home determines commute behaviour after the pandemic will in our expectations be somewhere in-between the pre-pandemic and post-pandemic relationships. We base this expectation on the indications that post-pandemic levels of working from home will be lower than during the pandemic, but higher than before the pandemic (Currie et al. 2021; Shortall et al. 2022).

Based on the literature, we expected that the complementary effect could partly be explained by the theory of constant travel time budgets, which states that people on average spend a similar, constant amount of time on total travel. If this is the case, then we would also find negative direct relations between commute and leisure travel time. We do indeed find a negative between-persons relation between commute and leisure travel time. This indicates that people who spend more time travelling for commuting spend less time travelling for leisure purposes. However, we find small but positive within-persons effects. This would indicate that the mechanism behind the theory of constant travel time budgets works on the between-person level, for example, due to negative between-persons feedback loops as a result of congestion or crowding. This would also indicate that research into the effectiveness of working-from-home policies on reducing total travel time should also rebound effects from people who do not work from home (Rietveld 2011). However, our within-person findings could be biased, either because people in a panel only get older and thus go through certain life events that might make them more or less mobile in general, or due to COVID-19 resulting in some people travelling less in general due to the threat of the virus.

Finally, we find that public transport commuters were much more likely to work from home more hours per week than non-PT commuters. Working from home has thus affected public transport commute travel time much more than travel time for the other modes. This finding is in-line with more descriptive analyses of the adoption and use of working from home because of the pandemic (Beck et al. 2020; de Haas et al. 2020) and studies showing that commuting demand for public transport will be most strongly affected (Bohman et al. 2021; Currie et al. 2021; Sweet and Scott 2022).

These conclusions have implications for policymakers, road authorities, and public transport operators. First, we do find that working from home reduces commute travel time. Working from home thus seems to be an effective strategy for policymakers to reduce peak-hour travel (which is largely based on commute travel) and thus congestion on roads and crowding in public transport. Critically, this recommendation depends on the assumption that our findings relating to travel time translate to decreases in travel distance. This might not necessarily be the case. We also find some evidence for between-persons rebound effects, which would also dampen the effectiveness of these policies. The within-person increase in leisure travel (found only before the COVID-19 pandemic) can also partly compensate for the reduced commute travel, but this shift will probably lead to a more spread-out activity pattern across the day and thus smaller peaks in travel demand. This finding is in line with expectations of the effects of the pandemic on travel behaviour in the literature (van Wee and Witlox 2021). It is important to note that working from home is only one of many factors affecting travel behaviour and that relevant actors should not overestimate its effects compared to all other factors that influence travel demand, such as broader economic or socio-demographic factors. Since the extent to which working from home determined commute travel time was much greater during the pandemic than it was before the pandemic, policymakers and transport operators should be careful when extrapolating the apparent influence of working from home on travel behaviour that we've seen during the pandemic to the post-pandemic future.

Following some limitations of the present study, future research is needed to further understand the relationship between working from home and travel behaviour. A few specific points to address are mentioned below. First, this study uses data from before and during the pandemic to set expectations for future relations between working from home. The

pandemic is not yet fully over, and it will be especially important to keep doing research into the relations as the world transitions out of the pandemic. Second, our study only partly addressed the heterogeneity of the impact of working from home concerning travel modes. More in-depth studies into the varying effects of working from home on especially public transport and active mode use would be a valuable addition. We did not account for other types of heterogeneity either, resulting in single estimates for the relations between working from home and travel time. There are at least two more interesting sources of heterogeneity to explore. First, studies could investigate potential differences between types of people, such as rural versus urban inhabitants or high-income versus low-income groups. Second, studies could explore whether there are differences between people who started to work from home during the pandemic and people who already worked from home before the pandemic started. This study used travel time to explore the relationship between working from home and travel behaviour: it would also be interesting to explore the effects on travel distance or number of trips using research methods that exploit the power of panel data. The last limitation of this study that we want to highlight here is that the effects are calculated using fixed timespans of one year between measurement waves. The effects of working from home are expected to vary over time, with people for example making different long-term decisions due to working from home. Hence, estimating the effects of working from home on travel behaviour using different spans of time could be a promising avenue for future research as well.

Appendix A: Schematic view of the estimated model
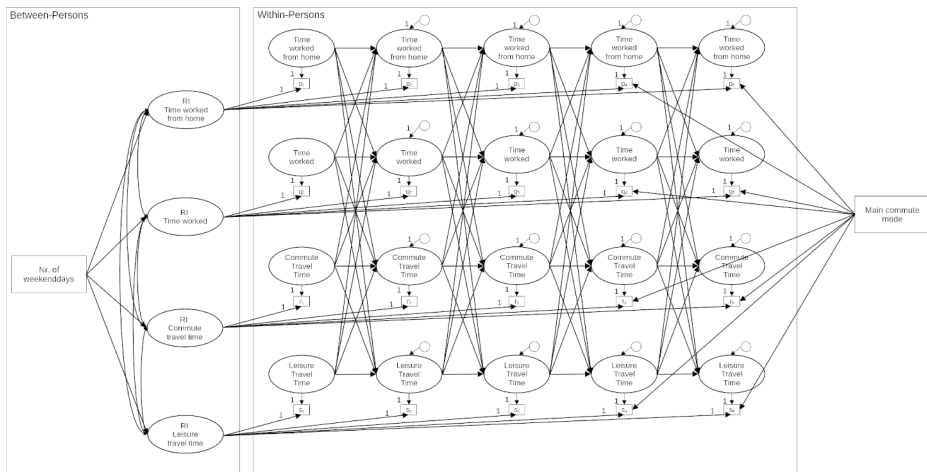
For the sake of visual clarity, correlations between variables and correlations between error-terms are omitted from this figure. The mean centring structure is also omitted. P_t, q_t, r_t and s_t, represent the measurements for the time worked from home, time worked, commute travel time, and leisure travel time respectively, where t refers to the wave in our study design.

Appendix B: Standardized estimates of the RI-CLPM

Table 7 Standardized parameter estimates for the first two wave-pairs

Inde-pendent variables	Dependent variables							
	First wave-pair (2017 → 2018)				Second wave-pair (2018 → 2019)			
	Work hours	WFH hours	Com-mute time travelled	Leisure time travelled	Work hours	WFH hours	Com-mute time travelled	Leisure time travelled
Time-variant variables								
Work hours	0.467	-0.057	0.019	-0.058	0.454	-0.054	0.017	-0.055
WFH hours	0.021	0.592	-0.113	0.042	0.026	0.695	-0.125	0.050
Com-mute time travelled	-0.006	-0.061	0.223	0.030	-0.007	-0.063	0.216	0.032
Leisure time travelled	-0.005	-0.028	0.044	0.061	-0.006	-0.033	0.049	0.072

In this and following tables, [***]$p<0.01$, [**]$p<0.05$, and [*]$p<0.1$

Table 8 Standardized parameter estimates for the last two wave-pairs

Inde-pendent variables	Dependent variables							
	Third wave-pair (2019 → 2020)				Fourth wave-pair (2020 → 2021)			
	Work hours	WFH hours	Com-mute time travelled	Leisure time travelled	Work hours	WFH hours	Com-mute time travelled	Leisure time travelled
Time-variant variables								
Work hours	0.220	-0.046	0.030	-0.024	0.210	-0.052	0.024	-0.021
WFH hours	-0.010	0.196	-0.134	0.014	-0.022	0.516	-0.251	0.030
Com-mute time travelled	-0.057	-0.149	0.169	0.073	-0.058	-0.179	0.144	0.070
Leisure time travelled	-0.072	-0.064	0.031	0.119	-0.078	-0.081	0.028	0.120
Time-invariant predictors								
PT Commuter[a]	0.026	0.140	-0.038	-0.010	0.026	0.161	-0.032	-0.010
Car Commuter[a]	0.021	-0.018	0.030	-0.021	0.022	-0.021	0.026	-0.020

In this and following tables, [***]$p<0.01$, [**]$p<0.05$, and [*]$p<0.1$

a. reference: all other travel modes as main commute mode

Declarations

Competing interests The authors declare no competing interests.

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