Longitudinal Analysis of Changes in Telecommuting Behavior and Associated Changes in Travel Behavior

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ABSTRACT

Due to the increased use of information and communication technologies, there has been a higher proportion of telecommuting in recent years. And the Covid-19 pandemic has massively accelerated this trend. With the higher proportion of telecommuting, there is an increasing need to study the effects of telecommuting on travel behavior. While previous studies have mainly focused on differences between telecommuters and non-telecommuters, it is important to understand if travel behavior is driven by the characteristics of telecommuters themselves or if telecommuting induces a change in travel behavior.

In this paper, we analyze panel data from the last ten years of the German Mobility Panel, a national household travel survey. A first-difference regression model is applied to assess changes in telecommuting and travel behavior beyond commuting of individuals. We estimate five different models to account for both long-term and short-term changes and changes in the telecommuting proportion itself.

The results show that long-term decisions such as residential relocation and car ownersip are not immediately affected by a change in telecommuting frequency. However, in a short-term perspective, changes in travel behavior become evident. While the number of trips decreases with the proportion of working from home, the person kilometers show a positive association. The results indicate that the differences between telecommuters and non-telecommuters stem mainly from re-investing the time saved by telecommuting into longer non-work-related travel and not from behavioral differences between the two groups.

Keywords: telecommuting, behavior analysis, German Mobility Panel, first-difference model, working from home**,** panel analysis, longitudinal

INTRODUCTION

The effects of communication technology on transportation systems have been studied for over 50 years (*1*). Because peak hour traffic caused by employees commuting to their workplaces remains a problem to this day, telecommuting, i.e., the act of working from (a location close to) home instead of traveling to work, has been a focal point of the discussion around travel substitution effects induced by communication technology.

Especially early studies assessing the effects of telecommuting on transport energy use and emissions predicted positive outcomes (*2*). However, during the more recent years, there has been a debate on whether telecommuting reduces travel and subsequently greenhouse gas (GHG) emissions. While previous research outcomes generally agree that telecommuters conduct fewer commuting trips compared to non-telecommuters (see e.g., (*3*–*5*)), studies on the relationship between telecommuting and non-work trips as well as person miles/kilometers traveled (pmt/pkt) present ambiguous results. While studies report a reduction of non-commute trips and total distances traveled (*5*–*7*), other work contradicts these findings as non-work trips and distances offset the savings from not commuting (*3*, *4*, *8*–*11*). The controversy around transport effects induced by telecommuting is further exacerbated by the complex relationship between telecommuting and residential relocation of employees (*12*–*14*).

Although there is an extensive body of research concerning these effects, most studies present results from comparisons between travel behavior of telecommuters and non-telecommuters and, thus, fail to account for individual-level changes in travel patterns induced by a change in telecommuting behavior. However, transport planners and policy makers are interested in understanding if and which effect an increase or decrease in telecommuting has on individual travel behavior. This is needed to help discern if telecommuters generally present certain travel patterns (compared to non-telecommuters) driven by their sociodemographic profiles (high-income, male, white-collar industry workers) as suggested by (*15*) or if the actual act of telecommuting promotes these patterns. This is especially important considering the vast increase in teleworkers resulting from the Covid-19 pandemic. Workplace closings were one of the main policy measures to reduce the spread of the virus in many countries, especially in the beginning of the pandemic (*16*). This resulted in a vast increase in telework. While the possibility to work from home (wfh) remained limited by the type of job, this possibility was at least partly extended to groups of employers who were previously unlikely to telecommute (*17*, *18*). This highlights the importance of needing to understand if travel behavior is driven by the characteristics of telecommuters themselves or if telecommuting induces a change in travel behavior.

Few studies address the change in telecommuting and travel behavior, which is likely attributed to inadequate data sources. To analyze change over time on an individual level, longitudinal data is needed which is scarcely available within the field of transportation research (*19*). The first study assessing the impacts of change in telecommuting was conducted in California in 1990. Kitamura et al. find that increasing telecommuting reduces work trips and does not induce additional non-work trips (*20*). A similar experiment was conducted in the Netherlands in 1991 in which Hamer et al. find that telecommuting reduced total distances traveled, the number of commute trips as well as non-commute trips (*5*). Although Gubins et al. also use longitudinal data to analyze commuting behavior, they only regard changes in travel behavior and not changes in telecommuting. Their results are in line with previous research showing that telecommuters increase their commuting distance compared to non-telecommuters (*21*). De Vos et al. present the only recent study addressing both telecommuting changes and subsequent commuting behavior changes. Based on the Dutch Labour Supply Panel, they show that switching to work from home leads to employees accepting longer commuting times and furthermore, commuting time increases with every additional eight hours of telework (*22*).

To add to these findings and to better understand the relationship between telecommuting changes and travel behavior beyond commuting, we analyzed data from the Germany Mobility Panel (MOP) of the last ten years. This paper presents the results of first-difference estimations on changes in work from home proportion, residential relocation, change in the number of household cars, number of weekly trips and weekly person kilometers traveled.

The remainder of this paper is structured as follows: We first provide an overview of the survey design of the German Mobility Panel and the data preparation steps we performed to generate the sample for our models. We go on to describe the method of the first-difference estimation. Subsequently, we present and discuss the estimation results. We conclude this paper by addressing shortcomings of our study and subsequent perspectives on future work as well as implications of our study for transport planners and policy makers.

MATERIALS AND METHODS

In this section, we first describe the data used for our analyses and how we prepared the data. We then describe the statistical model approach of the first-difference estimation.

German Mobility Panel

The analyses are based on the German Mobility Panel (MOP) data, a longitudinal national household travel survey. The survey is conducted on behalf of and funded by the German Federal Ministry of Transport and Digital Infrastructure. The Institute for Transport Studies of the Karlsruhe Institute of Technology (KIT) is responsible for the survey design and scientific supervision (*23*, *24*).

Since the start of the survey in 1994, the survey design is twofold: Firstly, respondents participate for three consecutive years and secondly, respondents also keep a trip diary for seven consecutive days. Approximately 3,000-3,400 respondents aged ten years and older in 1,800-2,000 households contribute to the survey each year. The survey period is in the fall and excludes any holidays to best capture everyday travel. The trip diary collects information on trip distances, mode of transportation, trip purposes and start and arrival times. Furthermore, sociodemographic information about the participants (e.g., employment status, gender, age), car and bicycle availability, public transport passes, and certain characteristics of the transportation system facilities (e.g., parking space availability at home and at work) are captured.

Furthermore, survey participants are asked to report any anomalies such as illness, vacation, and days their car was in the shop. Our analyses are based on the data from the 2012 – 2019 cohorts, reporting in the years 2012 until 2021, e.g., the data of the 2019 cohort were collected in 2019, 2020 and 2021. Figure 1 shows the sample size of each cohort and of each year. Because strong virus containment measures for the Covid-19 pandemic were in effect in Germany in 2020 (*25*), data from the 2020 survey are not included in the analysis.

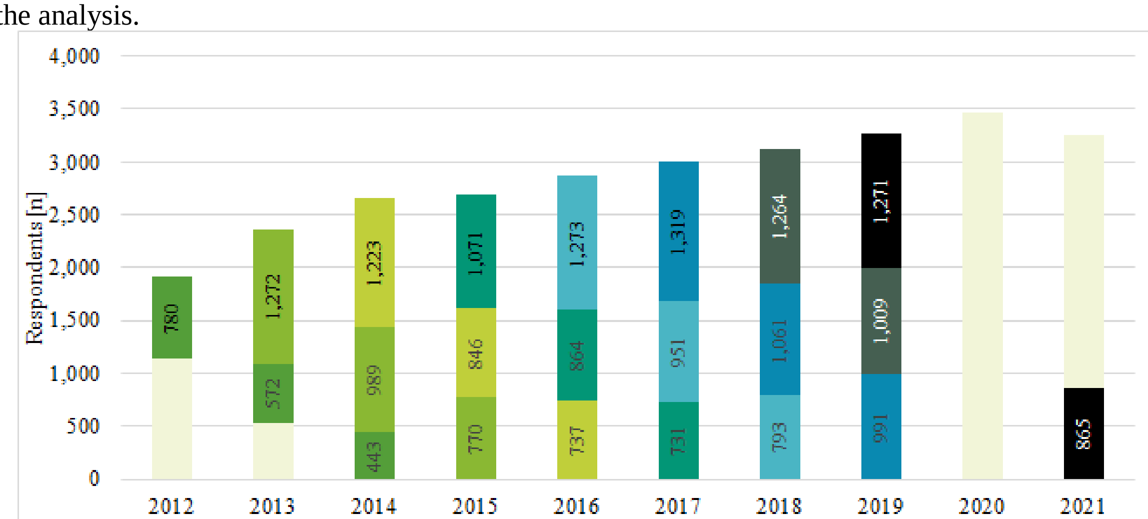

Figure 1: Study sample of the 2012-2019 cohorts from the German Mobility Panel (each color presents one cohort; respondents in off-white bars are not used in the analysis)

Data preparation and variables

While the MOP data is quite extensive, to analyze change in behavior, we first had to prepare the data and derive some of the variables. Data preparation was conducted using the programming language *R* (*26*).

The data from the survey is delivered in several datasets of which we used the household data, the person data, the children data and the trip data. All datasets share at least one common identifier (the household id) and the trip and person data additionally include a person identifier within each household. The identifier remains the same for the three years report for individuals and households so that they can be identified in subsequent years. Using these identifiers, we created a dataset in which each row corresponds to one person and year. We have chosen to analyze changes on a person-level rather than the household-level as drop-outs of respondents within households would have significantly reduced the available sample when calculating household-level travel behavior.

The sociodemographic variables of change, i.e., those that can change between two survey waves, we included in the dataset and subsequently in the analyses:

- Household size
- Number of household members over 10 years old
- Number of household members 10 years old and younger
- Number of children not in formal childcare
- Number of children in nursery childcare
- Number of children in primary school
- Household income
- Number of household cars
- Residential relocation
- Job change

Furthermore, we included variables to analyze changes in telecommuting and travel behavior:

- Number of weekly trips
- Weekly person kilometers traveled (excluding commuting distance)
- One way commuting distance
- Working from home frequency
- Working from home proportion as the share of number of days per week telecommuting over the total numbers of working days per week

While the number of weekly trips and weekly person kilometers traveled are easily calculated through summation across trips and distances traveled over the week for each person, both the working from home frequency and the commuting distance have to be derived from the travel diary as they are not explicitly asked for in the survey. To derive the one-way commuting distance, we selected the first commuting trip of each day (if present) and determined the mean commuting distance of all days on which a commute was reported. To later account for commuting distance and person kilometers traveled as both dependent and independent variables in the same model, we have subtracted the commuting distance from the person kilometers traveled.

The working from home frequency is only calculated for respondents who reported that they at least sometimes telecommute and who are full-time employed. For these, we first determined the number of workdays per week while assuming that a full-time employee works five days a week. From this number, we deduct the number of days on which at least one commuting trip was conducted. To control for other reasons why respondents may not report a commute to work, we assessed whether they reported any sick days or holidays. Instead of filtering out those who did report anormal days (sick days, holiday), we opted to use the telecommuting proportion on all workdays over the telecommuting frequency.

Statistical model approach

The changes in telecommuting behavior and subsequent changes in travel behavior were analyzed using a first-difference regression approach. In this model approach, the changes of both the dependent and independent variables over time are determined by calculating the difference of values between two survey waves and regressing the changes of the dependent variables on the changes in independent variables using ordinary least square (OLS) estimation:

$$y_{it} = X_{ijt}\beta_j + C_{ik}\beta_k \tag{1}$$

$$y_{it-1} = X_{ijt-1}\beta_j + C_{ik}\beta_k \tag{2}$$

$$\Delta y_i = y_{it} - y_{it-1} = X_{ijt}\beta_j - X_{ijt-1}\beta_j = \Delta X_{ij}\beta_j \tag{3}$$

Where *y* is the dependent variable, *X* the matrix of time-variant independent variables, *C* the matrix of time-invariant independent variables and β the coefficients estimated through OLS. The indices refer to *i* individuals, *t* year of survey, *j* time-variant parameters and *k* time-invariant parameters. By differencing equations (1) and (2), all time-invariant variables (both unobserved and observed) are removed, as we can see in equation (3). This means that the models only include time-variant variables and all constant variables such as gender were excluded from the estimation. To account for both long-term and short-term changes as well as to analyze changes in the telecommuting proportion itself, we estimated five models:

1. Changes in the working from home proportion
2. Residential relocation
3. Changes in car ownership
4. Changes in number of weekly trips
5. Changes in weekly kilometers traveled.

We estimated all models using the R package *plm* (*27*). The results of the estimation are presented and discussed in the following section.

RESULTS AND DISCUSSION

In this section, we describe and discuss the results of our analyses. We first present the findings of each model separately and conclude this section with overarching implications and shortcomings of our study. The results of the first-difference estimations are presented in TABLE 1.

Variable	Model 1: Wfh proportion	Model 2: Res. relocation	Model 3: Household cars	Model 4: Number of trips	Model 5: Person kilometers[1]
Intercept	0.0071*	0.024***	0.016**	-0.958***	-16.847**
Wfh proportion (wfh prop)	*n.a.*	-0.0004*	-0.036	-2.851***	294.351***
Household size		0.015*			-42.014***
# of hh members over 10 y/o			0.289***		
# of hh members 0-10 y/o			0.297***		
# of children not in childcare	0.12876***				
# of children in nursery	0.0890***				
# of children in primary school	0.0455***				44.355*
Household Income		0.005**	0.021***		
# of household cars			*n.a.*	0.658*	
Res. Relocation (reloc)	0.0107*	*n.a.*			54.790
Change of employers (coe)	0.0293*	0.089***			
Commuting distance (cd)					1.532***
Interaction: coe:reloc	-0.095***				
Interaction: wfh-prop:coe		-0.098***			
Interaction: cd:reloc					-4.109***

Significance at the ***1%-, **5%-, *10%-level

TABLE 1: First-difference estimation results

[1] without commuting trips

Model 1: Change in working from home proportion

In the first model, we analyze time-variant factors associated with an increase or decrease in the share of telecommuting days over all working days. The results indicate that the working from home proportion increases with an increased number of children present in the household. This confirms the association between positive attitudes towards telework for employees with small or dependent children at home as presented in previous studies (*28–30*). Interestingly, the magnitude of this effect changes depending on whether children are at home (not in childcare), in nursery and in primary school, indicating that the older children in the household get, the propensity to increase the telecommuting proportion decreases. The parameter for change of employer is positive, meaning that a new workplace is associated with an increase in telecommuting. This indicates that employers are more attractive if they offer flexible work arrangements. This is in line with results presented by Thompson and Aspinwall, who show that the choices of job applicants are significantly influenced by telecommuting opportunities (*31*). The parameter for residential relocation is positive but by itself not statistically significant. Interestingly, when included as interacting with a change of employers, the parameter is negative. Because both the change in employers and residential relocation only take positive values when differencing, this means that when somebody moves and changes employers the wfh proportion decreases. This may be explained by the fact that if employees decide that changing employers is worth moving, they might be more likely to go into the office to meet new people. Another possible explanation is that moving may not be the sole decision of the analyzed person on the individual level but a joint decision of the household. Thus, an explanation of a decreasing wfh proportion in the interaction effect of change of employers and residential relocation may also be the inflexibility in the choice of the employer when moving to a new place induced by another household member. Thus, maybe a new employer is chosen who does not allow telecommuting as much as the previous employer. In their study, Yao and Wang show that household relocation is often a matter of finding a balance between fairness and efficiency when household members choose a new residence (*32*). Our results indicate that the possibility to telecommute may be evaluated as less important in this decision-making process.

Model 2: Residential relocation

In the second model, we focus on residential relocation, i.e., how a change in the independent variables is associated with moving. Similar to the first model, the results show no statistically significant relationship between an increase in wfh proportion and moving. The results from both the first and second model are consistent with previous studies on the relationship between telecommuting and residential relocation (*12*, *14*). However, when considering the change in wfh proportion interacting with changing employers, the model results show a negative parameter. This means that if a person changes employers and at the same time increases their proportion of telecommuting, they are more likely to stay at their current residence, indicating again that employers are more attractive when offering flexible work arrangements as it does not necessarily force job applicants to move for a new job. The parameters for change in household income and size are both positive. This corroborates previous studies on the relationship between moving and income which show that a higher disposable income is associated with a choice to move (*33*) and an increase in household income also increases the willingness to relocate (*34*). Further, we see a positive relation between changing employers and moving, which is also consistent with previously presented findings (*21*).

Model 3: Change in number of household cars

In the third model, we considered the number of cars in the household as the dependent variable. Again, the parameter of change of wfh proportion is not statistically significant. Previous studies find a positive association between telecommuting and car ownership: O'Brien and Aliabadi suggest that telecommuters are more likely to own a car as they generally present with longer commuting distances (*35*) and O'Keefe et al. find that individuals with three or more cars are most likely to telecommute compared to other car ownership levels (*6*). However, our results do not corroborate this assumption but neither do our findings show a decrease in car ownership with an increase in telecommuting proportion. Our results further show positive estimates for the number of people in the household, considering both children under the age of 10 and household members aged 10 and older. This confirms previous research, which shows that increased family size is associated with a higher probability of purchasing a car (*36*). The same holds true considering an increase in household income: with a positive change in household income, the number of cars is also likely to increase. These findings are again in line with previous research (*36*).

Model 4: Change in number of conducted trips

In models 4 and 5 we investigate changes in travel behavior. In model 4 we analyze the change in number of conducted trips as the dependent variable. The results show that people who increase their telecommuting proportion decrease the number of weekly trips. In contrast, if the number of cars in the household increases, the individual is likely to also increase the number of trips. None of the other variables show a statistically significant effect on the change in number of conducted trips.

These findings indicate that the results of previous studies on the difference between trip rates of telecommuters and non-telecommuters (*3, 4, 8, 11*) stem from a direct behavioral change induced by a change in telecommuting behavior and are less likely due to other differences between the two groups.

Model 5: Change in person kilometers traveled

In model 5 we analyze the person kilometers as the dependent variable. Regarding the wfh proportion we see a different effect than in model 4. While the number of trips decreases with a higher wfh proportion, the person kilometers strongly increase.

It should be highlighted that when calculating the person kilometers traveled, we excluded the travel performance related to trips to work. Taken together with results from model 4, we can conclude that the people who increase telecommuting, decrease trips in their everyday travel, but travel longer distances. This result may be explained by the stable travel time budgets hypothesis (*37*). The time saved in not commuting during peak hours can be invested in other activities, e.g., traveling to places for recreation. People likely travel for leisure activities in less busy hours compared to commuting, meaning they can travel longer distances in the same amount of time. Thus, the person kilometers per person increases. This outcome is contrary to the findings presented by He and Hu who found that behavioral changes result from differences between telecommuters and non-telecommuters and not from freed-up time through telecommuting (*15*). However, Bunitz et al. have suggested that telecommuting increases temporal flexibility allowing for a variety of other activies (*3*). Our findings support these results.

The identified interaction effect between commuting distance and residential relocation further corroborate the relationship between the decrease in commuting time and increased kilometers traveled. The parameter is negative, which means that when a person moves and thus, decrease their commuting distance, their overall kilometers traveled increase using the freed-up time of a shorter commute to travel further for other activities. Another possible explanation is that after moving, people are more likely to keep going to their former destinations out of habit (e.g. supermarkets) or because they still conduct some of their leisure activities closer to their old home.

Surprisingly, when regarding commuting distance by itself, the results indicate a positive relationship between the commuting distance and the total person kilometers traveled during a week (excluding kilometers traveled for commuting purposes). While this is counterintuitive when considering the previously described results, it should be noted that an increase in commuting distance does not automatically imply an increase in commuting time. Thus, the previous arguments could still hold in this case if e.g., the increase in commuting distance is the result of a switch to a faster commute mode albeit on a longer commute route.

Further, model 5 shows that the traveled distances decrease when the household size increases. This may indicate that with an increasing number of household members, trips for running errands are distributed among them and thus the individual-level kilometers traveled decrease. In the model results, we see a positive parameter for change in the number of children in primary school. Because children in primary school also start to be active in other social activities such as sports or music lessons, the distances traveled by their parents may also increase as they escort them to these activities.

Implications and limitations of the study

The results of the five models have several overarching implications for policy makers, transport planners as well as future research. Our results show that a change in telecommuting intensity does not significantly influence residential relocation or car ownership, implying that there is at least some inertia when it comes to long-term decisions. We suggest that policies geared towards telecommuters should encourage employees to reduce the number of cars. A way to accomplish this is by going specifically through firms which could limit the possibility of getting a company car or a parking space at the office depending on the telecommuting frequency.

This is especially important as our results show a strong relationship between an increase in telecommuting and person kilometers traveled. Taken together with the lack of influence on car ownership, the increase in person kilometers traveled could be at least in part increased vehicle kilometers. While more research is needed to confirm this assumption, based on these preliminary findings, we suggest that policies promote modal shifts for non-work activities such as incentives for public transport tickets. As telecommuters reduce the number of commuting trips, they are less likely to benefit from public transport season tickets which can often be used for non-work trips as well.

It is interesting to note that household size and composition were significant in one way or another in all five models. This highlights the complex decision-making process in both long-term (residential relocation and car ownership) as well as short-term (telecommuting frequency, number of trips and personal kilometers traveled) travel behavior. This is especially important for transport planners who want to analyze the effects of telecommuting and subsequent behavioral changes on the transport system. We suggest including household configuration and interdependent behavioral patterns in travel demand models at a high level of detail.

Furthermore, our findings regarding a decrease of the number of trips with an increase in telecommuting proportion have implications for the transport system as a whole: if the number of telecommuters increases on a scale that leads to noticeably less commuting traffic, travel times during peak hours are reduced as well. Transport planners and policy makers should be aware that this could lead to a modal shift towards less environmentally friendly modes as the car becomes more attractive to non-telecommuters.

There are also some shortcomings of the study worth noting. The data used for the analyses of this paper is based on a travel survey conducted in the same design for over 25 years and is mainly focused on travel behavior rather than telecommuting behavior. While respondents are asked if they work from home, they do not indicate whether they telecommuted on specific survey days. Although control for reasons of abnormal travel behavior, the telecommuting frequency is a derived variable and may be inaccurate for some respondents. This also limits the analyses to respondents who are employed full-time and who work from home all day compared to part-time telecommuting. Along the same lines, we also have to derive the commuting distance which is only available if observed and no explanation is given if the commuting distance varies without changes in job or residential relocation.

Further, we are unable to control for time-variant variables not observed in the survey. Although major life events such as the birth of a child or job changes are recorded, it remains unclear if and which other factors change could induce a change in travel behavior.

CONCLUSIONS

This study is one of few assessing the change in telecommuting behavior and associated changes in travel behavior. We leverage the unique survey design of the German Mobility Panel in which respondents repeatedly report their travel behavior over one week in three consecutive years. Our results show that long-term decisions of residential relocation and changes in employers are not associated with a change in telecommuting frequency. However, the short-term travel behavior changes travel show a significant association with a change in working from home proportion.While a decrease in number of trips is associated with higher proportion of telecommuting, person kilometers traveled increase. This indicates that the differences between telecommuters and non-telecommuters stem from re-investing the time saved by telecommuting into longer non-work travel and not from behavioral differences between the two groups.

Our findings contribute to the recent debates on the telecommuting effects on transport. Furthermore, this paper sheds new light on how long-term changes in telecommuting participation resulting from the Covid-19 pandemic will change travel behavior.

The analyses presented in this paper have put focus on the induced changes in travel behavior which should be explored in more detail in future studies. We suggest that changes in mode choice behavior should be explored to investigate if the increased distances are traveled by less ore more environmentally friendly modes to further inform policy makers. As our results show, changes in travel behavior are likely due to changes in time use of freed-up commuting time when switching to telecommuting. Future analyses should explore this relationship in more detail. Further, these changes in telecommuting behavior should be integrated into a travel-demand modeling framework which could help assess changes on the transport network as a whole. Lastly, a statistical modeling method allowing for a more in-depth causality analysis such as path-analysis models could supplement this work.

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AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: A. Reiffer, L. Ecke, M. Magdolen, P. Vortisch; data collection: A. Reiffer, L. Ecke; analysis and interpretation of results: A. Reiffer, M. Magdolen, L. Ecke; draft manuscript preparation: A. Reiffer, M. Magdolen, L. Ecke. All authors reviewed the results and approved the final version of the manuscript.

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