Daniel Heimgartner

Measuring and Modeling the Impact of Telework on Transport Demand - Data, Tools and Analysis

Diss. ETH No. ?

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presented by

DANIEL HEIMGARTNER
MSc. Economics
Stockholm School of Economics

born on 22 August 1992
citizen of Switzerland

accepted on the recommendation of

Prof. Dr. D. Kaufmann, examiner
Prof. em. Dr. K. W. Axhausen co-examiner
Prof. Dr. T. Bernauer, co-examiner
Prof. Dr. M. Bierlaire, co-examiner
Prof. Dr. S. Hess, co-examiner

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To whom it may concern

ABSTRACT

This dissertation investigates the adoption and impacts of telework on transport demand in Switzerland. It addresses four research questions regarding telework's adoption brought about by the pandemic, identifying the population who teleworks, its management via employer-side incentives and its effect on time allocation, mobility and, ultimately, transport demand. The thesis employs a combination of survey, tracking and time-use data, as well as stated preference experiments. Key methods used are discrete choice models, generalized linear models and ordered probit switching regression – a form of endogenous switching regression. The study finds that telework adoption increased by 15 percentage points during the pandemic, though current employer constraints (binding for around one fourth of the teleworking population) limit further adoption. Hybrid work policies provide only little leverage, highlighting that employees value their baseline telework preferences highly. Telework seems to segment the population, with usual teleworkers (3+ days/week) being relatively more mobile (at counterfactual same telework intensities) and having a preference for public transport as a commuting mode. Meanwhile, overall modal shares are surprisingly stable across teleworker groups and mobility tools are only rebalanced at high telework frequencies (4+ days/week, which is the exception). There, the main adjustments are substituting public transport national and regional subscriptions for the half-fare card. No clear substitution pattern for car can be identified. A key contribution of this work is the development of the **OPSR** R-package, implementing the ordered probit switching regression framework, addressing selection bias when treatments are ordinal and self-selected and the outcome is continuous. The method is applied to simultaneously model telework adoption and weekly kilometers traveled, accounting for error correlation between the two processes. The results suggest that telework can substantially reduce weekly mileage (by -16%, comparing the current telework situation to the no telework reference), offering a tool for mitigating transport-related negative externalities. While the theory underlying OPSR dates back to Heckman's seminal work from the 1980s, this thesis demonstrates, that the method is still essential today with applied research often overlooking the possible concern of selection bias. However, this can lead to contradicting policy recommendations and may explain conflicting findings on telework's impact on transport demand.

ZUSAMMENFASSUNG

Deutsche Zusammenfassung hier.

ACKNOWLEDGEMENTS

I would like to thank ...

CONTENTS

NOTATION

FREQUENTLY USED ABBREVIATIONS

TW	telework
TWers	teleworkers
TWing	teleworking
NTW	non-telework (0 days/week)
NUTW	non-usual telework (<3 days/week)
UTW	usual telework (3+ days/week)
TE	treatment effect
ATE	average treatment effect
MTMC	mobility and transport microcensus
MNL	multinomial logit
OPSR	ordinal probit switching regression
OL	ordinal logit
RQ	research question

R CODE

R code and its output is formatted verbatim

```
R> f <- function() {
+    cat("Hello, world!\n")
+    1 + 2
+  }
R> f()

Hello, world!
[1] 3
```

1

INTRODUCTION

The definition of insanity is doing the same thing over and over and expecting different results.
— Albert Einstein

1.1 BACKGROUND AND MOTIVATION

The transport sector contributes 15% of global greenhouse gas emissions (IPCC, 2022), with emissions at 31% being significantly higher in Switzerland (BAFU, 2024). Meanwhile, reducing it through policies such as road pricing or fuel taxes is unpopular. Similarly, being mobile yields great utility and behavioral adjustments such as reducing leisure travel or choosing greener transport modes are difficult.

The COVID pandemic enforced such behavioral change and constrained our free movement. Meanwhile, economies adjusted quickly and shifted to remote work wherever possible, quadrupling the home office share in just a few quarters (for the case of US, see Barrero *et al.*, 2023). Telework (working from home, home office) was largely successful and popular and it was clear that the new work form, to some extent, would be integral part of our everyday work-life. However, three questions emerged: First, what population share would telework after mandatory lockdowns and restrictions were lifted, second, to what degree would they telework and third, what is the impact of telework on transport demand beyond the pandemic circumstances?

Scholarly work investigating this relation dates back to the revolution of information and communication technology (see Salomon 1986; Nilles 1988; Mokhtarian 1991 for early work). However, findings regarding the direction of effect have always been debated (Hook *et al.*, 2020).

This might not be surprising, as the relation between telework and transport demand is intricate with second-order effects potentially offsetting reduced commuting. Telework is more than a change of workplace. For example, more freedom in time-allocation might induce non-work travel, teleworkers might find new mobility tools attractive, or they might even relocate. In fact, de Vos *et al.* (2018) find that teleworkers accept longer commutes, i.e., they commute less frequently but when they do, they travel further.

Another possible explanation, is, the different methods employed – some more suitable than others. As we will argue, telework can be seen as a self-selected treatment (see Section 1.4 for the conceptual framework) and as such, requires causal inference methods from the program evaluation literature.

1.2 OBJECTIVES

As we are now aware, the pandemic worked as a catalyst in telework adoption. During the crisis, telework was used to avoid travel and contact with other people, thereby containing the spread of the virus. Anyone who could telework should (or rather had to) do so as much as possible. However, it was clear that once such telework recommendations or duties were lifted, there would be some backlash. In that context I ask

RQ1: How did telework adoption change over the course of the pandemic in Switzerland?

RQ2: Who are the teleworkers? Who has the option to telework, who wants to telework and how much?

RQ3: How can telework be managed? Can employers entice employees back to the office once lockdown measures are lifted?

RQ4: What is the impact of telework on transport demand?

The operationalization of these research questions as well as the hypothesis posited are stated in the individual chapters. The nature of the thesis is empirical and I try to be methodologically rigorous. An objective of this thesis is also to contribute to R's (R Core Team, 2024) ecosystem and develop statistical packages if implementations are missing.

R code is integral part, embedded throughout the text. Both input and output is formatted verbatim

```
R> f <- function() {
+    cat("Hello, world!\n")
+    1 + 2
+  }
R> f()

Hello, world!
[1] 3
```

1.3 THEORETICAL BASES AND METHODOLOGY USED

Methodologically, all papers employ discrete choice models (e.g., Train, 2009) or some form of generalized linear model (e.g., Venables and Ripley, 2002). These include ordinal probit or logit, multinomial logit, the multiple discrete-continuous extreme value model and random error component extensions. The fourth research question, being concerned with treatment effects, then draws heavily on the program evaluation literature. In particular, a form of endogenous switching regression is employed. As we will argue, the treatment is not exogenously prescribed but self-selected and therefore is related to Heckman's seminal work (Heckman, 1979) on selection bias.

As is clear for the technical reader, defining characteristic of such probability models is always the assumed error distribution. I think that this assumed error distribution is the (latent) main character in this thesis and plays an important role in almost any chapter. I hope that after having read this thesis, sentences such as "where we assume that the errors are independent" are questioned or at least cautiously read.

1.4 CONCEPTUAL FRAMEWORK TO UNDERSTAND TREATMENT EFFECTS AND SELF-SELECTION

Let's assume for conceptual clarity that we observe three different groups A, B and C in a world where telework is unheard of (yet technologically perfectly feasible). These three groups might be very different socio-economically and also in terms of their mobility behavior. We now treat a random third of each group with "non-usual" telework (NUTW; say 2 days/week), another third with "usual" telework (UTW; say 3+ days/week), and leave the rest untreated ("non" telework, NTW). We could then test whether or not there are within (e.g., A_{NTW} vs. A_{NUTW} vs. A_{UTW}) and across group differences (e.g., A_{NTW} vs. B_{NTW} vs. C_{NTW}) with respect to a metric of interest such as kilometers traveled (where A_{NTW} are the weekly kilometers traveled by an NTW-treated individual A). I.e., we could test, whether both the treatment and/or the treatment effects depend on the group receiving it.

Our world differs in two crucial regards: First, we can not randomly prescribe a treatment such as telework (it already has been prescribed by nature) and second, nature rarely prescribes a treatment randomly. As a consequence, answering the above question in our world is not as trivial as in teleworkomania. We only observe, say, A_{NTW}, B_{NUTW} and C_{UTW} and it is spurious (while tempting) to assume $A_{NTW} = B_{NTW}$. Somewhat more subtle (and therefore even more tempting) is to assume that $A_{NTW}(X) = B_{NTW}(X)$, i.e., differences in the outcome of interest can be attributed to observables. This thesis makes a point that unobserved factors influencing the group allocation (A, B, C) might be correlated with unobserved factors influencing the outcome. This correlation needs to be accounted for!

For example, cyclists riding without a helmet (the "untreated") might be young and have a risk-seeking tendency. We therefore potentially overestimate the benefit of wearing a helmet if we compare the accident rate and/or crash severity rate between those who wear and do not wear helmets directly. Even if we may control age for the comparison, variables such as risk-seeking are not readily measured, and it may still be part of the error in applied research and thus leading cause of a selection bias.

1.5 OUTLINE OF THE THESIS

This thesis is structured as follows: Chapter 2 analyses changes in mobility behavior brought about by the pandemic descriptively and investigates modal shares before, during and after the pandemic in Switzerland. Telework is identified as the main constituent of a "new normal" (if such a name is even deserved, as the analysis reveals). Chapter 3 updates the relation between survey response burden and response rate – a simple framework to estimate ex-ante survey completion. Chapter 4 introduces the **snndata**, the most complete telework-related dataset for Switzerland, allowing researchers to investigate telework behavior, the importance of employer incentives (work arrangements) and the relation between telework and mobility tool ownership. Chapter 5 leverages this data and explores how hybrid work policies influence telework frequency, emphasizing the role of incentives. Chapter 6 introduces the **OPSR** R-package, a toolbox for estimating ordered probit switching regression (OPSR) – a form of endogenous switching regression. This enables us to conduct the main analysis of this thesis in Chapter 7 where we estimate the effects of telework on transport demand. Chapter 8 demonstrates various estimation and post-estimation routines as part of the **OPSRtools** R-package, completing the **OPSR**-universe. Chapter 9 summarizes the thesis and concludes.

Chapters 4, 6 and 7 are the heart of this thesis and responsible for its title – data, tools and analysis.

2

MODAL SPLITS BEFORE DURING AND AFTER THE PANDEMIC

The key is not to predict the future, but to prepare for it.

— Perikles

The MOBIS-Covid data provides a unique opportunity to put mobility adjustments observed during the crisis in perspective. A large panel has been tracked from before the crisis up until the end of 2022. Starting with 1'370 participants and observing a gradual drop-off, around 250 kept tracking throughout the whole study period of over 2 years. Switzerland lifted its measures counteracting the virus spread in mid-February 2022, reaching a potential new equilibrium in the months after. Descriptive indicators have been constructed for Switzerland in order to disentangle the narrative of the crisis from the perspective of transport demand. The descriptive findings are supplemented by a mixed multiple discrete-continuous extreme value model (MMDCEV). We find a shift in modal splits away from car and train, where in particular bus could expand its mode share. While the cycling and walking booms were temporary, the bicycle still shows slightly higher mode distance shares. There are observable differences between the working arrangements (home office, mixture and in-office), however, we do not find evidence that preferences differ substantially. This suggests that the working arrangement segments the population along socioeconomic dimensions with different mobility behaviors and mode preferences. Modes are more satiated in the post-pandemic world, hinting that people use fewer modes in their weekly modal mix but use them more intensely. However, the model suggests that the pandemic should not be read as a structural break in mode preferences. We will therefore likely see further convergence to the pre-pandemic equilibrium.

This chapter is based on the following paper

Heimgartner D. and K. W. Axhausen (2023) Modal Splits Before, During, and After the Pandemic in Switzerland, *Transportation Research Record*, **2678** (7), 1084–1099.

Author contributions Study conception and design: all authors; data collection: D. Heimgartner; analysis and interpretation of results: D. Heimgartner; draft manuscript preparation: all authors. All authors reviewed the results and approved the final version of the manuscript.

The following changes were made Figure 2.1 and Table 2.2 were improved for readability; *Work-outside-home* was relabeled to *Office* both in the figure legends and text; A short introductory text after Section 2.3 was added.

2.1 INTRODUCTION

The COVID Pandemic hit our system from various angles: First and foremost, it was a health crisis with risk asymmetries between different groups in society. It was a considerable shock to our economies with high uncertainty and supply chains breaking down. Firms have proven to be very flexible, adopting working from home, keeping productivity at high levels. Last but not least, the initial solidarity seemed to fade with the duration of the crisis and political polarization peaked with the vaccine roll-out. Not surprisingly, almost all of these dimensions played into our mobility behavior in one way or the other, either directly (e.g., because of health concerns) or indirectly (e.g., by reducing commuting activities through working from home).

Several studies have been trying to describe the evolution of transport demand during early stages of the crisis and by different means such as tracking studies or questionnaires. But of course, all the effects outlined above, were intertwined and a clear attribution was difficult. Therefore, it has not been possible to answer the question of whether or not these patterns have persisted in the post-pandemic world.

The MOBIS-Covid study (Molloy *et al.*, 2022) provides a unique opportunity to look at the persistence of these effects. A Swiss panel with comparably rich socioeconomic information has been tracked from before the crisis until today. In Switzerland, all restrictions and measures to contain the spread were lifted on February 17, 2022, and we potentially converged to a new equilibrium in the months that followed. Therefore, we have revisited the MOBIS-Covid data and tried to comment on how sustainable initial findings have proven to be and translate to recent times. For this purpose, a comprehensive set of descriptive indicators has been constructed in order to disentangle the narrative of the crisis. Special emphasis is given to the question of how new hybrid working arrangements (i.e., home office) drive modal splits (as measured by mode distance shares). The descriptive findings are strengthened by a mixed multiple discrete-continuous extreme value model (MMDCEV) where we model both the discrete and continuous dimension of weekly mode distance shares and compare the pre-pandemic to the arguably post-pandemic world.

2.1.1 *Covid-19 timeline in Switzerland*

Based both on the COVID case numbers and the measures imposed to counteract the spread of the virus, the following six phases can be distinguished. The phases are visualized together with COVID case numbers (rolling 14-day mean) in Figure 2.1. The narrative of the pandemic is presented hereafter and summarized in Table 2.1, where each phase of expansion (constraining the free movement) is followed by a phase of relaxation.

1. Phase (restriction): COVID reached Switzerland in early 2020. The situation deteriorated quickly and by March 20, 2020 over 4'800 people infected. This first phase can thus be characterized by a rapid spread of the virus as well as high uncertainty. On March 16, 2020 the Federal Council declared an extraordinary situation, which allowed it to introduce uniform measures in all cantons. A lockdown was imposed, closing all non-essential businesses, along with schools, recreational facilities and public parks. As a consequence, employers were urged to reorganize the working hours of their employees to avoid rush-hour travel. Home office was implemented, wherever possible. The measures were extended until April 26, 2020 after which the Federal Council followed a strategy to gradually emerge from the lockdown in three stages.

2. Phase (relaxation): The gradual easing of the enforced measures ended on June 6, 2020, when all events up to 300 people and spontaneous gatherings for up to 30 people were allowed again. High schools and universities were able to resume, and all leisure and entertainment businesses as well as tourist attractions re-opened. Relatively calm summer months followed, suggesting that the spread of the virus might follow seasonal patterns.

3. Phase (restriction): Beginning October 19, 2020, a series of measures was introduced again as the situation worsened. Home office was recommended, culminating in a home office duty starting January 18, 2021. The duty was in place until June 26, 2021.

4. Phase (relaxation): However, even before abolishing the home office duty, other measures constraining the free movement of people were gradually eased as the third COVID wave was rather shallow. That is, while commutes were still reduced during phase 4, leisure activities were not. Again, the summer months were relatively calm.

5. Phase (restriction): With the onset of autumn end of September 2021, the last expansionary phase started. New, aggressive COVID variants emerged. As vaccination was fully rolled out with all the residents having had the opportunity to get vaccinated twice, a COVID certificate was required starting September 13, 2021. Political polarization was a consequence with society being divided into two segments with different constraints. However, home office became mandatory again for all, as of December 20, 2021 and was in place until February 3, 2022.

6. Phase (relaxation): Despite rocketing case numbers, the path back to normalization started in February 2022 (as intensive care stations were not at limiting capacities any longer). Almost all measures have been abolished by February 17, 2022. As the transition to a relatively normal life might have taken some time, we define the normalization phase to begin March 1, 2022.

The *baseline* period is defined as all data points before October 31, 2019. The period from November, 2019 to the onset of the pandemic in late February, 2020 is discarded as a randomized controlled trial was conducted and mobility patterns are expected to be governed by the treatment.

2.2 RELATED WORK

In this section, we review studies that explore the impact of COVID on mobility patterns with a focus on modal shifts. Whereas changes during the pandemic are well understood, literature that looks beyond the crisis is sparse due to obvious reasons. Nevertheless, some work has been identified that tries to generalize the initial findings to an environment without COVID restrictions.

Phase	Start	End	Description	Evolution
1	2020-02-28	2020-04-26	1. Wave: Onset of the pandemic, high uncertainty, lockdown	Restriction
2	2020-04-27	2020-10-18	Calm summer months	Relaxation
3	2020-10-19	2021-02-28	2. Wave: Home office recommendation followed by requirement (mid January)	Restriction
4	2021-03-01	2021-09-12	3. Wave: Shallow third wave, calm summer months	Relaxation
5	2021-09-13	2022-02-28	4. Wave: Spread of the Omicron variant, home office and certificate requirement	Restriction
6	2022-03-01	2022-06-29	Normalization	Relaxation

TABLE 2.1: The evolution of the pandemic in six phases.

Paul *et al.* (2022) present a review of the global findings on changes in transportation behavior due to the COVID pandemic. During the pandemic, a reduced usage of public transportation could be observed while reliance on private cars increased. While this is a global pattern, non-motorized vehicle usage and walking prevalence increased mostly in European countries. Trips for some particular purposes have remained high using only a specific mode of transport. Several studies report a decrease in commuting which can be attributed to either job loss or an increase in working from home. Similarly, sociodemographic attributes determine the trip frequency – among others mediated by home office access. Risk perceptions play an important role too.

Abdullah *et al.* (2020) report that trip purpose, mode choice, distance traveled, and frequency of trips were significantly different before and during the pandemic. Shopping trips were the dominant trip-generating purpose. A shift from public transport to private and non-motorized modes could be observed. This can be attributed to people placing a higher priority on health related concerns when choosing a mode during the pandemic.

Molloy *et al.* (2021b) use the MOBIS data set (Molloy *et al.*, 2022) and conduct comprehensive descriptive analysis in order to report the impact of restrictive measures during the pandemic on mobility behavior. Reductions of around 60% in the average daily distance were observed, with decreases of over 90% for public transport. Meanwhile, the cycling mode share increased drastically. Modal shifts were considerable, especially for public transport subscription holders. The change in modal shares was particularly pronounced when restrictions were imposed and somewhat less so after restrictions were eased. However, pre-pandemic levels were never reached during the study period. The authors further find that home office is effective for suppressing travel demand with effects persisting over the enforced home office restrictions. The authors discuss long-term policy implications. However, the time-window from the onset of the pandemic until the middle of August 2020 was rather short and extrapolation beyond the pandemic situation has to be seen in that perspective. As we use the same data set and conduct very similar descriptive analysis, our work puts these preliminary findings in context and scrutinizes whether or not the observed changes during the pandemic were made habitual.

Meister *et al.* (2022) employ a mixed multiple discrete-continuous extreme value model (MMDCEV) to estimate mode distance shares for an urban population. Separate parameters were derived for four distinct segments, from September 2019 until the end of 2020 (still amid the crisis). Their findings confirm global trends: A substantial decrease in public transport usage (50% depression at the end of their sample period), recovered car usage (with a temporary increase of 40% during the pandemic) and a cycling boom (increase in travel distance up to 150% and frequency increasing by 40% during summer). The model sheds insights on a change in user group composition for PT and cycling.

Currie *et al.* (2021) is one of the few studies that pursues the question of whether post-pandemic travel behavior will be different from pre-pandemic travel. The study relies on survey data where respondents were asked to reveal their future expectations. PT ridership will recover but is not expected to reach pre-pandemic levels. The mode share of car will increase and offset reduced congestion due to working from home resulting in a net increase of car usage and higher peak volumes. Although the study was conducted in Melbourne, their results seem to generalize and support the findings by Shamshiripour *et al.* (2020) and Beck *et al.* (2020).

To summarize, the general narrative reveals a modal shift away from public transport to car and in particular to non-motorized forms of transport. Even though home office might reduce peak volumes, congestion on roads might increase due to a net increase in individualized transport. Sociodemographic peer groups adjust mode usage differently, mainly due to different risk perceptions (during the pandemic) or home office access. Previous work either extrapolated findings during the pandemic to the post-pandemic world or relied on respondents' expectations.

2.3 METHODS

In the following, we first introduce the data and conduct comprehensive descriptive analysis for various mobility indicators before elaborating on the MMDCEV modeling framework.

2.3.1 *Data*

Starting in September 2019, a sample of 5'375 Swiss residents were recruited to take part in a mobility pricing field experiment called MOBIS. Using an app, the participants tracked their location and thereby mobility and activity patterns could be identified. They were tracked for 8 weeks in an ambition to investigate their response to a conceptual mobility pricing scheme in a randomized controlled trial. Participation and tracking numbers are depicted in Figure 2.1, together with COVID case numbers and the six phases outlined before.

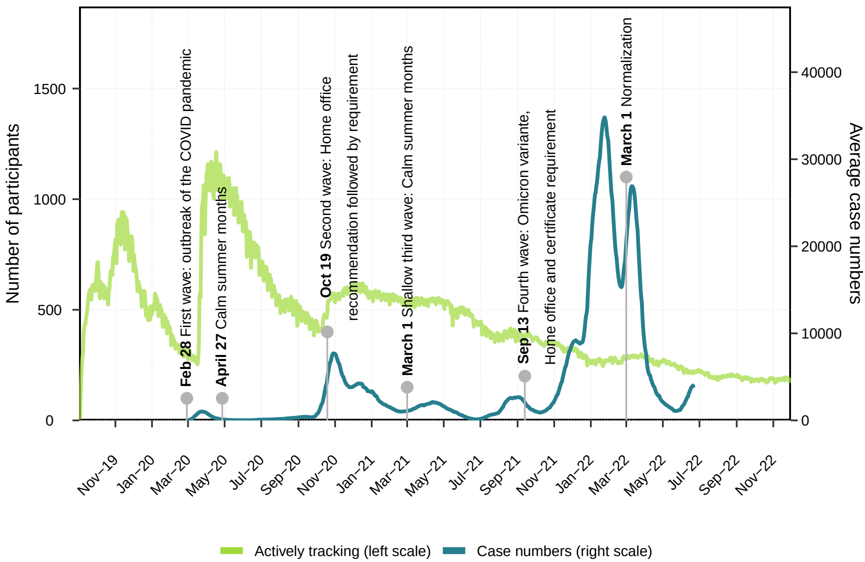


FIGURE 2.1: Covid case numbers and timeline.

The 3'680 participants who completed the MOBIS study, were asked to reactivate the app in an effort to understand mobility behavior during the pandemic. Around 1'600 volunteered to do so building the panel of the MOBIS-Covid19 study that underlies this report.

People were only eligible to participate in the MOBIS study if they used a car at least 2 days a week. This skewed our sample towards car drivers. However, comparing the sample to the last mobility and transport micro census 2015, the MOBIS-Covid19 sample was found to be broadly representative of the Swiss population (Molloy *et al.*, 2021b).

Since January 2021 we observe a gradual drop-out of participants as no further recruitment efforts have been made. Nevertheless, around 250 people are still using the app as of today. This raises the concern of a potential self-selection bias. To make statistics comparable over the full time horizon a re-weighting scheme is applied, comparing the characteristics of the remaining individuals against the original 22'000 participants who filled out the introductory survey. Weights are based on age, gender, income, education, mobility tool ownership and accessibility and are calculated for each person-week.

The socioeconomic characteristics were collected in several surveys during various stages of the study. While some of the questions were included in several survey instruments, it is important to acknowledge that for most of the variables, we do not have longitudinal information. That is, only one particular point in time is reflected and some of the attributes might have changed over time. For example, the working arrangement variable {Home office, Mixture, Office} is based on two work-related surveys, fielded in April 2021 (Phase 3) and October 2021 (Phase 4), where respondents were asked how many days a week they work from home or in office respectively. Therefore it most certainly happened that some of the people were labelled home working in Phase 3 or 4 but switched back to in-office without us noticing. Nevertheless, the working arrangement variable can be seen as a proxy.

2.3.2 *Descriptive analysis of mobility patterns*

In this section the evolution of different mobility patterns is described. Different correlation patterns shed light on a possible narrative accompanying the evolution during the six phases (Table 2.1). We first elaborate on activity spaces before looking at various mode-specific patterns.

For all the time-series graphs moving averages (with a window size corresponding to 30 days) were computed in order to filter the noise. For most figures, the evolution is both depicted in absolute numbers, comparing the average of the different phases (bar charts) as well as in relation to the baseline period, reflecting percentage deviations (line charts). Dotted vertical lines segment the time axis into the seven phases (each segment corresponding to one bar). Triangles mark end of September days which is the mid-point of the baseline (and should therefore be comparable beyond seasonal patterns). Squares mark the end of the timeline, emphasizing the relative evolution since the beginning of the pandemic. The reader should keep in mind, that the baseline is a rather arbitrary point in time (e.g., capturing the seasonal patterns of Switzerland's autumn months) before the pandemic.

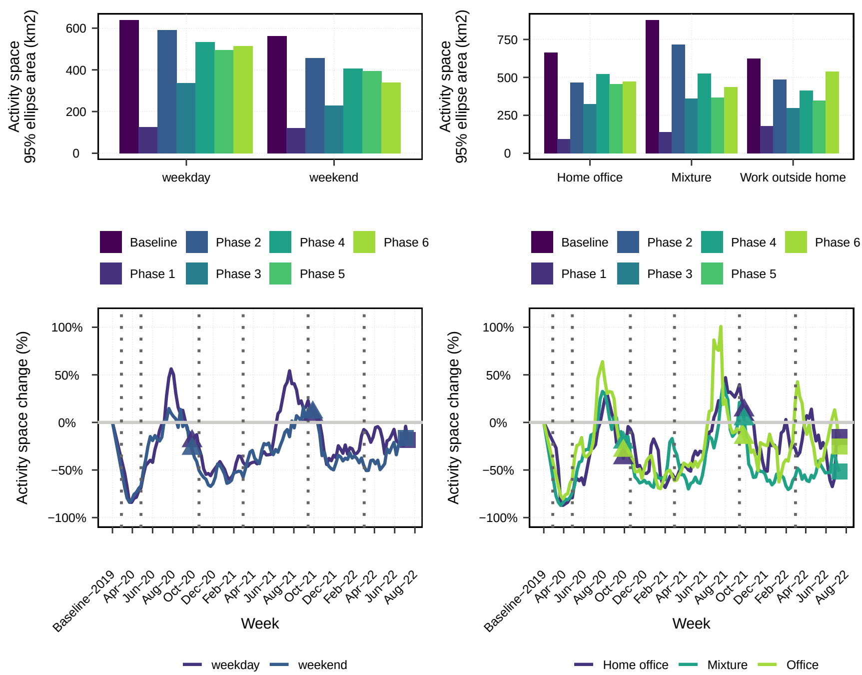


FIGURE 2.2: Change in activity spaces.

Not surprisingly, activity spaces, as measured by the 95% CI Ellipse area, were considerably depressed during the pandemic and are strongly governed by imposed COVID restrictions (Figure 2.2). Seasonal patterns might exaggerate the effects of the pandemic with prevalence being higher during winter months where activity spaces usually are smaller. However, recent levels have not yet reached pre-pandemic ones. The home office population reduced activity spaces more pronounced at the onset of the crisis but had slightly larger activity spaces compared to the in-office peers in the calm summer months (phase 4). However, in the normalization phase, the activity spaces of the in-office population are again the largest. Therefore it is not fully clear, whether home office depresses activity spaces in normal times. Further, considerable pre-pandemic differences in the levels exist: The participants working partly remotely and partly in-office had much larger activity ellipses in the baseline. Again, it is pivotal to understand, that these people were not necessarily working in a mixture working arrangement before the crisis, but did so at the time of the survey. Nevertheless, it highlights, that the working arrangement segments the population and impacts transport demand via depressing activity spaces of particularly mobile groups (with large activity spaces).

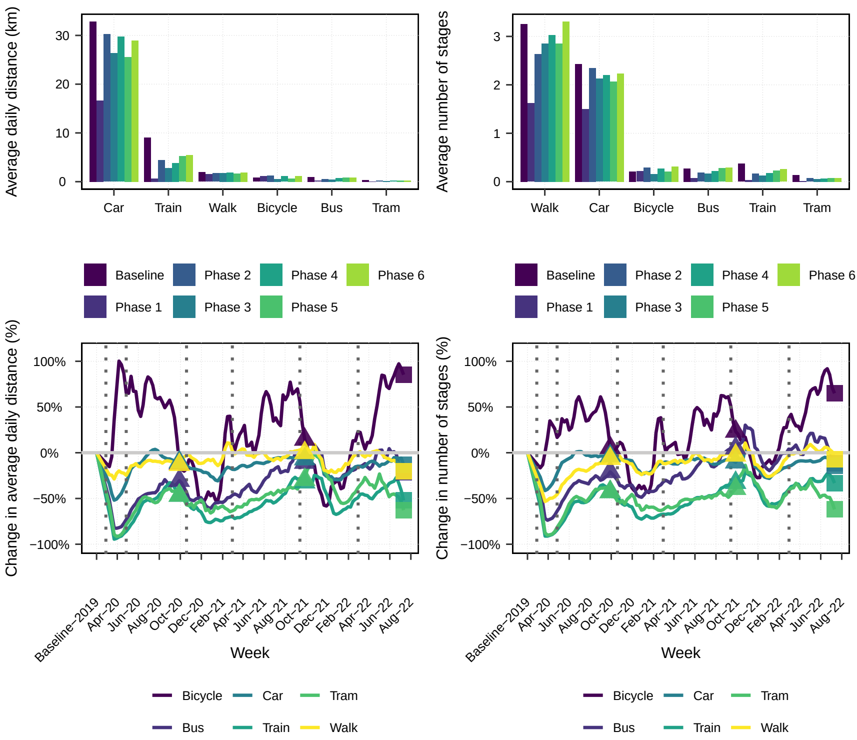


FIGURE 2.3: Change in average daily distance and number of stages by mode.

In Figure 2.3 the change in average daily distance as well as the change in number of stages by mode is depicted. A stage is the movement with one means of transport including possible waiting times, contrasting a trip, which is a sequence of stages from one activity to the next. All the modes react strongly to the evolution of the pandemic with bicycle being the only mode that shows cyclical (correlated with case numbers) patterns and walk being relatively stable. Public transport (PT: bus, train, tram) was considerably hit and has not yet recovered from the shift induced by the pandemic with bus being the exception. Daily distance and number of stages show very similar patterns with similar magnitudes (percentage deviations). Together with Figure 2.2 it could be argued that individuals tend to stay in closer proximity to their home location and therefore bicycle and bus are comparatively more frequently used (with the personal bicycle being available more freely).

A very similar picture is portrayed in Figure 2.4 where we show average stage lengths and the average number of stages per day and by mode. The bicycle boom described by various authors (e.g., Molloy *et al.*, 2021b; Meister *et al.*, 2022) has its foundation in the peek visible in the year 2020 and the fact that bicycle is the only mode that benefited from restrictive measures. Despite bicycle stage lengths not reaching these very high levels, it is still the case that bicycle usage is slightly higher than during the pandemic. In particular, it is used more frequently. On the other hand, train travel has considerably reduced but is on a steady upward trend ever since. The reduction was primarily caused by fewer travels and not necessarily by shorter travel distances. One explanation could be that annual subscriptions (which reduce the marginal cost of PT travel considerably) got cancelled in times of high uncertainty making the mode less attractive accompanied by hygiene concerns.

Similarly, when differentiating by working arrangement, the collinearity between daily distances and number of stages is evident (see Figure 2.5). Both distances and number of stages could be reduced most pronounced by *Home office* during the onset of the crisis. While the number of stages reached pre-pandemic levels for all working arrangements, daily distances did not for the more home-based peer groups. That is, the home office population was more mobile before the crisis. Looking at absolute levels, shows, that people doing home office during the crisis had a higher average daily distance in the baseline, potentially not because of the work situation but other moderating (socioeconomic) factors. Considering the latest phase, all working arrangements share similar levels. Therefore, one could again

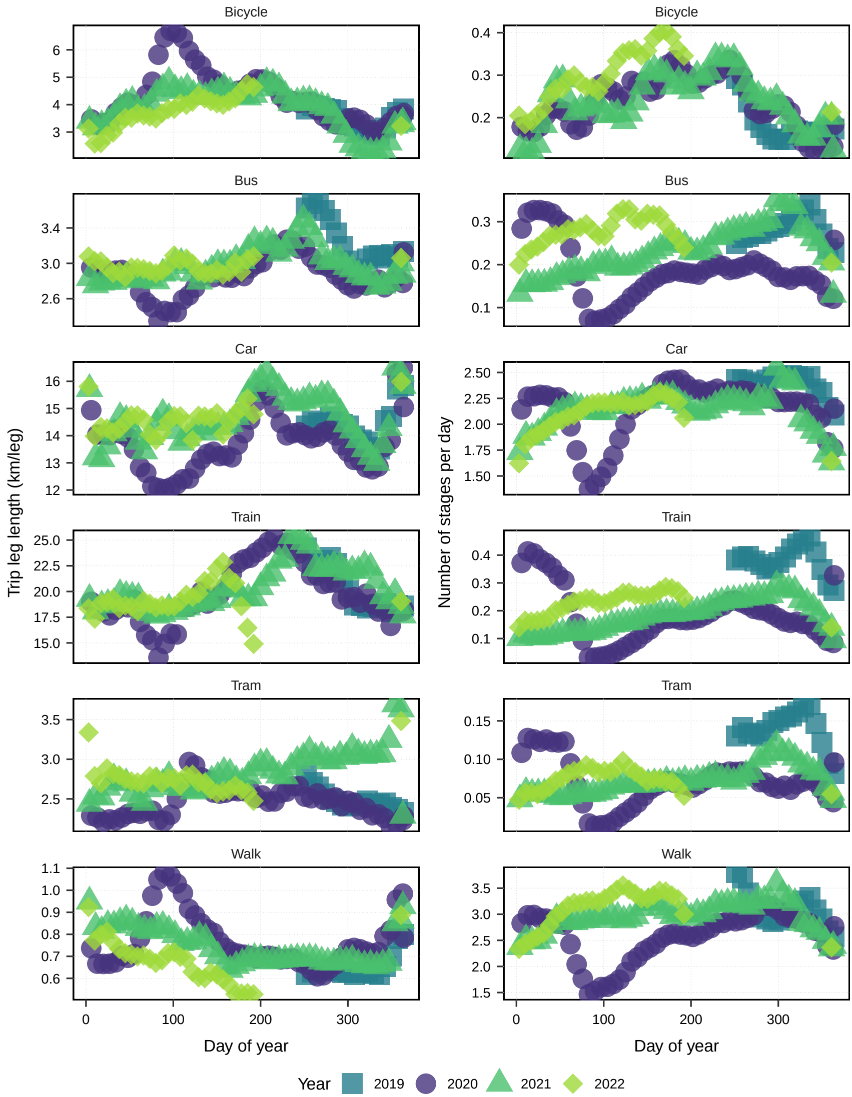


Figure 2.4: Average trip leg length and number of trips by mode. Comparison year on year.

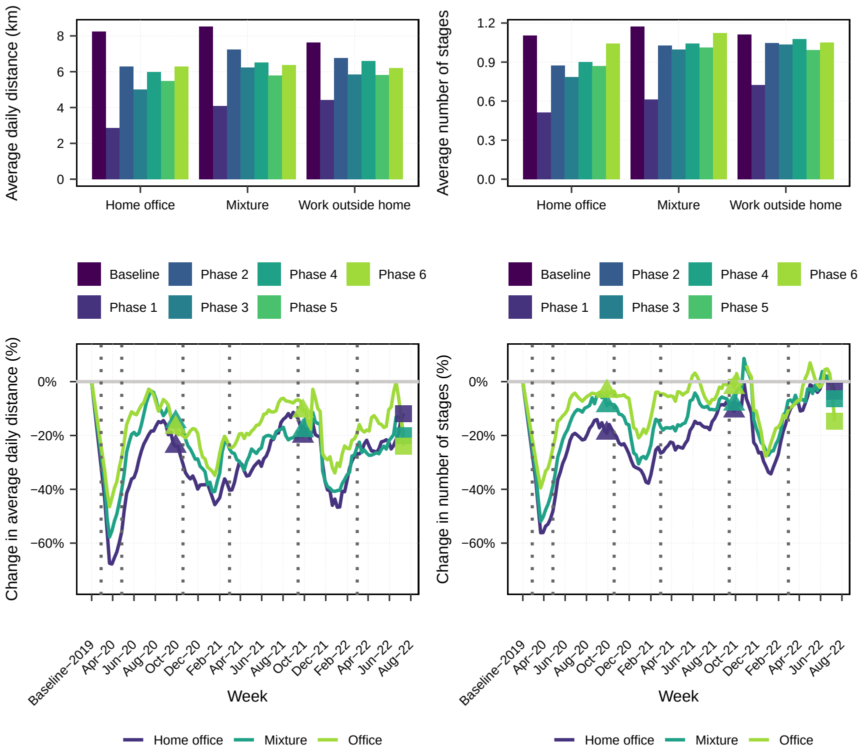


FIGURE 2.5: Change in average daily distance and number of stages by working arrangement.

conclude, that home office does depress transport demand not because the home office population travels less but because they would have traveled particularly much in the absence of the hybrid working arrangement (e.g., due to long commuting distances which they now can avoid).

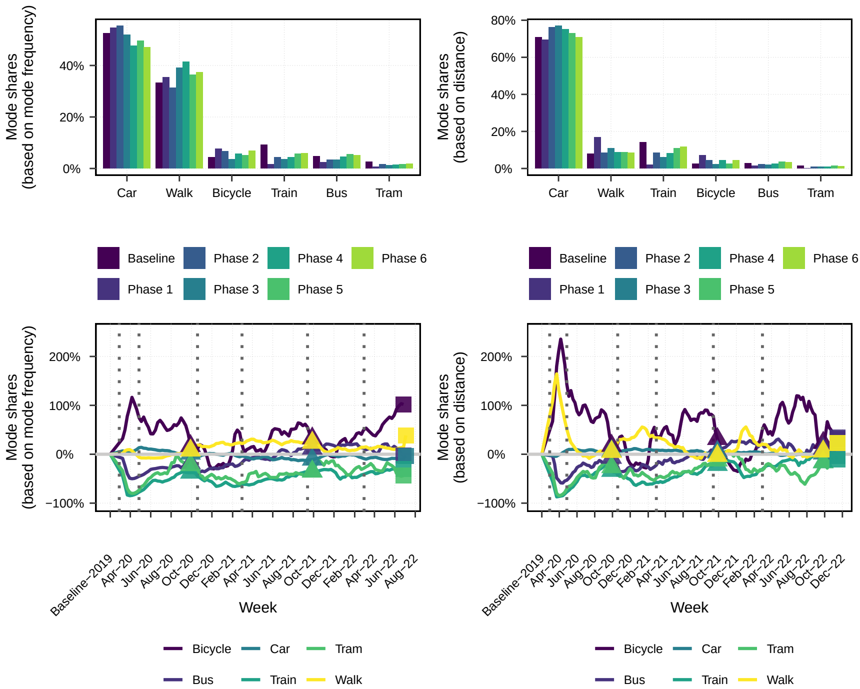


FIGURE 2.6: Mode shares by distance and mode choice frequency.

Shifting attention to mode shares, Figure 2.6, we constructed two indicators: Mode share based on how often a particular mode is chosen as the main mode (mode frequency) and mode share based on traveled distance. This reflects the two preference dimensions and both the intensive (choice frequency) and extensive (covered distance) margin as well as the relative importance of the different modes. Again, a strong collinearity between the two indicators can be observed. Bicycle could expand its mode share along both dimensions (and beyond purely seasonal trends). Walking and car depict the most stable mode shares with walking showing a pronounced peek in the distance share during phase 1 (as already noted in Figure 2.4). Interestingly, local public transport has been affected differently: Bus defended its mode share more rigorously whereas tram could not. Again, train steadily recovers from the big shock in phase 1 with a slightly higher recovery in its mode distance share. One explanation might be that people increased the number of short trips, where car and train are less likely to be considered.

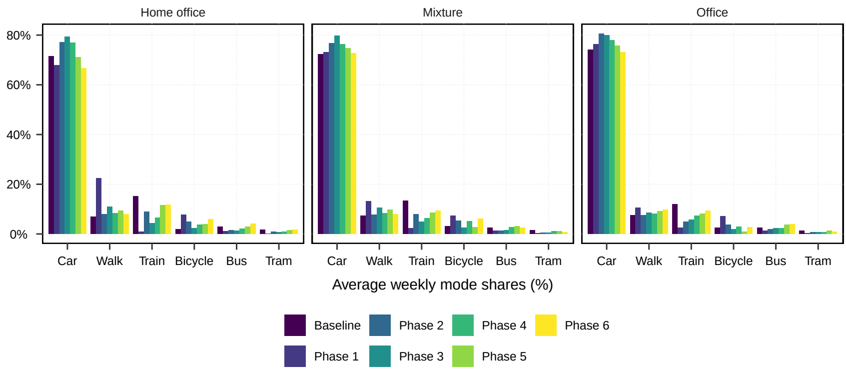


FIGURE 2.7: Mode distance shares by working arrangement.

Figure 2.7 reveals the following insights: First, modal splits do not dramatically differ between the working arrangements. Second, train has lower mode distance shares across all working arrangements, which could be due to ongoing hygiene concerns or a lagging recovery because of cancelled subscriptions which are now as so slowly renewed with decreasing uncertainty. Car increased the mode share only temporarily during the pandemic and the home office population shows a slightly lower car distance share in phase 6 (compared to the other working arrangements). On the other hand, train has a higher relative importance. As the average daily distance (see Figure 2.5) does not differ greatly in the most recent phase, we can conclude that the home office population has a slight preference for train. The walking boom during the onset of the pandemic can be attributed to the home office population.

Figure 2.8 shows the number of trips generated during a particular hour of the day and relative to the hour with the most trips (for each mode separately and differentiating weekdays and weekends as well as working arrangements). The left-hand side compares the data before COVID to the most recent values (after restrictions have been removed, i.e., phase 6) while the right-hand side is based on phase 6 only.

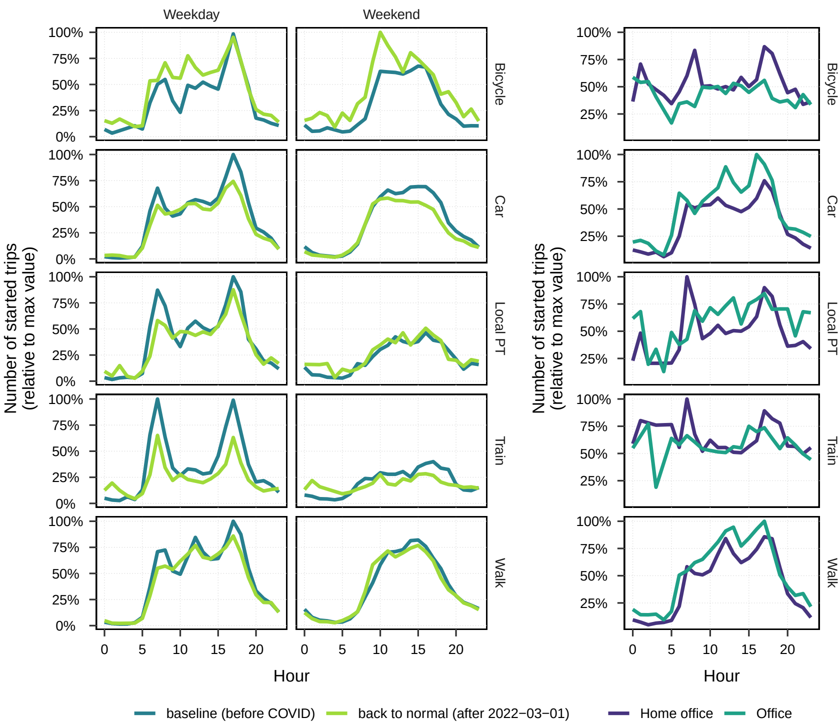


FIGURE 2.8: Hourly trip counts relative to most busy hour.

For example looking at row *Train* and column *Weekday*, most trips are generated during the morning and evening peak hours (which is the 100% reference hour) with the two peaks matching one another. Cycling increased during the day and weekends (but not during commuting hours). Car and train show more or less a parallel downwards shift. For train this shift is more pronounced than for car. The depression is less severe for local PT (bus and tram) than for train. For walk we see again the decrease during commuting peaks but otherwise, it is back to normal. Further, people working from home seem not to be that mobile during the day (most modes are almost identical during working hours, with bicycle being the exception). For car and train we see a decrease even during the weekend which either could imply that people reduced activities or stayed in closer proximity to home (as local PT does not show this decrease, while bicycle increases...).

The pronounced morning and afternoon peeks of the peer group *Home office* for PT might reflect that if they work from the office space they choose PT, i.e., the home office population does not necessarily switch to car but has simply reduced demand due to reduced commuting. On the other hand, we have seen that people working from home use more regional modes, in particular bicycle. The very similar trip generation of *Home office* compared to *Office* during working hours could again be interpreted, as the home office population not being that mobile during working hours.

The descriptive results are summarized below. The bicycle was the only mode used more intensively during restrictive phases. However, seasonal patterns could overemphasize this correlation. The bicycle boom was a temporary phenomenon that can be attributed to rather high stage lengths during the onset of the pandemic. Still, the bicycle is used more frequently in the normalization phase.

All PT modes (train, tram, bus) were considerably depressed by the pandemic. While train and tram have not yet fully recovered, bus did. Nevertheless, train is on a steady upward trend ever since the initial shock.

Mode frequency shares decreased for car and train. This could be a consequence of people conducting more shorter trips where bus and bicycle have the advantage over car and train.

The impact of home office on activity spaces is ambiguous. During the pandemic, home office was an effective tool to reduce transport demand. In the normalization phase, average daily distances and average number of stages are almost identical among the three working arrangements. We hypothesize that home office depresses transport demand not because of the home office population travels less but because they would have traveled particularly much in the absence of the hybrid working arrangement (e.g., due to long commuting distances which they now can avoid). Modal splits do not dramatically differ between the working arrangements with a slight preference for train for the home office workforce. Car on the other hand is used less intensively.

2.3.3 *MMDCEV modeling framework*

In this section, the econometric framework is introduced. The multiple discrete-continuous extreme value model (MDCEV) was first formulated by Bhat (2005). The model reflects on the fact that many consumer situations are characterized by multiple discreteness (a bundle of goods is consumed) of imperfect substitutes. In transportation, people choose both a portfolio of modes (discrete choice) and to what extent each mode is employed (continuous choice). Our formulation lends itself from Meister *et al.* (2022) and considers the two dimensions mode choice (discrete) and choice of weekly distance shares by mode (continuous). The MDCEV models require a budget constraint and mode shares naturally add up to 1 which is the total budget a person can attribute to the available modes. Further, the marginal rate of substitution is constant (if you decrease the mode share of train by 1% you necessarily have to collectively increase the mode shares of the other modes by 1%) which abstracts from the cost component, i.e., the budget line has slope 1. Such would not be the case if we would model weekly mileage by mode.

The original model formulation incorporates both a translation parameter gamma (allowing for corner solutions) and a satiation parameter alpha (governing the marginal utility). However, it is well-known (Bhat, 2008, e.g.,) that it is difficult to separate the two effects empirically (as the gamma parameter also has a satiation interpretation). Therefore, the modeler has to choose between three profiles (dropping or fixing one of the two parameters). We have estimated simple models with all the profiles and will from here onward only consider and present the so-called gamma-profile as it yielded the highest model fit.

In the following discussion of the panel MMDCEV model structure, individuals are indexed by $q \in \{1, \dots, Q\}$, weekly choice occasions by $t \in \{1, \dots, T\}$ and $k \in \{1, \dots, K\}$ indexes the travel modes. The vector of travel distance proportions in week t is $x_{qt} = \{x_{qt1}, \ldots, x_{qtK}\}$ (which sums to 1). Consider the following CES-type of additive utility function

$$U_{qt}(x_{qt}) = \sum_{k=1}^{K} \gamma_k \psi_{qtk} \ln\left(\frac{x_{qtk}}{\gamma_k} + 1\right). \tag{2.1}$$

The term ψ_{qtk} refers to the baseline utility and controls the discrete dimension, i.e., the utility that accrues to choosing alternative k in a particular week. As already discussed, γ both has a translation interpretation (corner solutions, 0 consumption) and in combination with the logarithmic transformation a satiation interpretation. The marginal utility is decreasing in γ which implies that higher values of γ stand for higher satiation (i.e., a higher distance mode share). The baseline utilities of the six modes are further given by

$$\psi_{qtk} = \exp(\theta_k + \beta z_{qk} + \mu_q s_k + \epsilon_{qtk}) \tag{2.2}$$

where θ_k reflects the inter-individual average utility of choosing alternative k, $z_q k$ is a vector of observed attributes and β the corresponding vector of utility weights. The term $\mu_q s_k$ stands for a random error component where μ_q is multivariate normally distributed and s_k is a column vector of dimension K. Each element of μ has a variance of σ_k^2 and is assumed to be independent of the other elements (i.e., the covariance matrix is diagonal) and hence captures pure inter-individual heterogeneity as a mixed component and is constant across time periods t. ϵ_{qtk} is idiosyncratic noise and follows a type I extreme value distribution (distributed iid across individuals, modes and choice occasions).

It can be shown that conditional on the random error component, the probability of observing individual q choosing mode k to have a share x in week t has the following solution

$$P(x_{qt}|\mu_q) = \left[\prod_{i=1}^{M} c_{qti}\right] \left[\sum_{i=1}^{M} \frac{1}{c_{qti}}\right] \left[\frac{\prod_{i=1}^{M} e^{V_{iqt}}}{(\sum_{k=1}^{K} e^{V_{qtk}})^M}\right] (M_{qt} - 1)! \tag{2.3}$$

where M is the number of alternatives chosen by individual q at choice occasion t. Discrete choice modelers can see the familiar ratio of exponential utilities in 2.3. Further

$$c_{qti} = \left(\frac{1}{x_{qti}^* + \gamma_i}\right) \tag{2.4}$$

for $i = 1, \ldots M$ and

$$V_{qtk} = \theta_k + \beta z_{qk} + \mu_q s_k - \ln\left(\frac{x_{qtk}}{\gamma_k} + 1\right). \tag{2.5}$$

The parameters to be estimated are the θ_k and γ_k scalars, the β vector as well as the σ_k^2 variance elements characterizing the variance matrix of μ. We choose the maximum likelihood inference approach where the likelihood for individual q's optimal distance share investment is given by

$$L_q(\theta, \psi, \beta | \mu_q) = \prod_{t=1}^{T_q} [P(x_{qt}^*, \theta, \psi, \beta | \mu_q)]. \tag{2.6}$$

The unconditional likelihood can be formulated by marginalizing over the random vector μ

$$L_q(\theta, \psi, \beta, \omega) = \int_{\mu} [L_q(\theta, \psi, \beta | \mu_q)] dF(\mu | \omega) \tag{2.7}$$

where F is the multivariate cumulative normal distribution. The log-likelihood function reads

$$LL(\theta, \psi, \beta, \omega) = \sum_q \ln[L_q(\theta, \psi, \beta, \omega)]. \tag{2.8}$$

We use the **apollo** R-package (Hess and Palma, 2019) and generate a Halton sequence of 1'000 inter-individual draws in order to approximate the integral in Equation 2.7. Our model-building strategy included testing different profiles, different levels for the discrete variables as well as gradually increasing the model complexity and excluding insignificant variables. This process involved data of the normalization phase only. We further constructed variables reflecting on the mode-specific accessibility, a person's living environment (e.g., degree of urbanization) and controlled for weather characteristics. However, we carefully checked for co-linearity and did not consider all the constructed variables (e.g., urbanization and access measures were closely related as well as temperature, humidity and pressure levels).

2.4 RESULTS AND DISCUSSION

We estimated the MMDCEV model based on the panel in the baseline and normalization (phase 6) periods, where separate parameters were estimated except for μ_q (capturing unobserved heterogeneity, panel effects and thereby introducing correlation between the two periods). We only considered weeks where respondents tracked every day, as our activity chains are hypothesized to repeat weekly and since daily mode share patterns can potentially differ greatly from weekly ones. This left us with a sample of 906 respondents (150 remaining in phase 6), providing collectively 8'711 weekly mode share vectors. The final model has 73 parameters per phase (plus five phase-generic ones) which are presented in Table 2.2 where we differentiate the two phases. Simple *t* tests for the parameter differences between the two time periods were computed. Values postfixed with a dagger (†) indicate that the difference is significant at the 5% level. Car is the reference alternative and coefficients have to be interpreted accordingly. For example, the ASC of bus has an interpretation of the bus' mode share relative to car. In the baseline, this constant is below 0 which indicates that car had a higher share. In the normalization period, it still is below the mode share of car (-1.2) but compared to the baseline, mode share diverted from car to bus. The dagger (†) indicates, that this difference is statistically significant.

	Car		Bus		Train		Tram		Bicycle		Walk	
	Estimate	Rob. se	Estimate	Rob. se	Estimate	Rob. se	Estimate	Rob. se	Estimate	Rob. se	Estimate	Rob. se
BASELINE												
Sigma	0.962^{***}	(0.223)	-1.245^{*}	(0.569)	-2.020^{*}	(0.876)	1.592^{***}	(0.256)	1.310^{***}	(0.350)	-0.113	(0.197)
Gamma	5.073^{***}	(0.723)	0.695^{***}	(0.078)	1.115^{***}	(0.095)	0.795^{***}	(0.050)	5.485^{***}†	(0.608)	0.012^{***}	(0.003)
ASC			-2.780^{***}†	(0.672)	-4.366^{***}	(0.974)	-5.122^{***}	(1.195)	-3.752^{***}	(0.323)	3.113^{***}	(0.306)
MIV accessibility			0.017	(1.159)			-0.911	(0.469)			-0.187	(0.181)
General accessibility			0.160	(0.088)	0.191^{***}	(0.037)	0.225^{***}	(0.051)	0.119	(0.094)	0.153^{***}	(0.043)
Below 46					-0.203	(1.516)						
Commute days			0.079	(0.047)	0.067	(0.062)	0.155^{*}	(0.076)	0.090^{*}	(0.036)	-0.025	(0.017)
Employed			-0.195	(0.211)			-0.041	(0.496)	-0.096	(0.267)		
Full-time employed			0.027	(0.883)	-0.572	(0.523)	-0.043	(0.319)	-0.105†	(1.053)	-0.075	(0.361)
Has GA			1.291^{**}†	(0.399)	-0.060†	(0.679)	3.018^{***}	(0.341)	2.365^{***}	(0.698)	0.848^{**}	(0.267)
Has regional PT			1.238^{***}	(0.227)	0.169	(0.544)	1.928^{***}	(0.272)	1.393^{*}	(0.645)	0.822^{***}	(0.173)
Has half-fare			0.133	(0.175)	0.195	(1.645)	0.617^{**}	(0.209)	0.706^{*}	(0.283)	0.067	(0.114)
HH size below 3					-0.378	(0.239)			-0.093	(0.270)		
Male											-0.079	(0.136)
Mean tempearture			-0.026^{**}†	(0.010)	0.018	(0.010)	-0.003	(0.007)	-0.015†	(0.009)	-0.005	(0.004)
Total precipitation			0.015^{*}	(0.007)	-0.044^{**}	(0.015)	0.007	(0.009)	-0.003	(0.007)	0.003	(0.004)
Home office			-0.253	(0.844)	0.204	(0.691)	0.006	(0.508)	0.130	(0.825)	-0.099	(0.228)
Home and office			-0.149	(0.259)	0.258	(0.749)	-0.050	(0.212)	0.175†	(0.302)	-0.117	(0.195)

Continued on next page

Table 2.2 – *Continued from previous page*

	Car		Bus		Train		Tram		Bicycle		Walk	
NORMALIZATION												
Gamma	7.522*	(3.685)	0.811***	(0.155)	1.448***	(0.347)	1.228***	(0.265)	10.035***†	(1.190)	0.013*	(0.006)
ASC			−1.197†	(0.815)	−3.899*	(1.718)	−4.833***	(1.439)	−2.798***	(0.444)	4.036***	(0.955)
MIV accessibility			−0.152	(2.954)			−2.111	(1.168)			−0.632	(0.393)
General accessibility			0.047	(0.051)	0.217*	(0.088)	0.276*	(0.131)	0.138**	(0.050)	0.157	(0.086)
Below 46					−0.016	(1.370)						
Commute days			0.033	(0.159)	−0.028	(0.327)	−0.022	(0.137)	−0.018	(0.195)	−0.041	(0.037)
Employed			−0.538	(0.656)			0.852*	(0.405)	−0.462	(0.734)		
Full-time employed			−0.220	(1.272)	−0.261	(1.009)	−0.777	(0.915)	−0.903†	(1.145)	−0.321	(0.210)
Has GA			−0.131†	(0.974)	1.220†	(0.650)	2.293	(1.941)	1.125	(0.732)	0.143	(0.542)
Has regional PT			0.326	(1.183)	0.050	(0.277)	1.274	(0.692)	0.744	(1.037)	0.570	(0.578)
Has half-fare			−0.573	(0.415)	0.271	(1.875)	0.483	(1.810)	0.523	(0.317)	−0.284	(0.620)
HH size below 3					−0.260	(0.549)			0.259	(0.277)		
Male											−0.162	(0.129)
Mean tempearture			0.025***†	(0.007)	0.047**	(0.016)	0.011	(0.036)	0.026**†	(0.009)	0.004	(0.005)
Total precipitation			−0.008	(0.011)	−0.015	(0.021)	−0.034	(0.033)	0.005	(0.019)	−0.010	(0.007)
Home office			0.214	(1.897)	0.001	(1.443)	−0.115	(0.656)	−0.026	(1.725)	0.053	(0.249)
Home and office			−0.394	(0.343)	0.344	(0.265)	−0.454	(0.687)	−0.544*†	(0.222)	−0.082	(0.180)

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1;

† Significant parameter difference at 5% level

Table 2.2: MMDCEV model estimates.

Because of a smaller sample size in the normalization period, 95% confidence bounds are much wider. Therefore, while (considerable) differences between the two phases exist, most of these differences are not significant. It follows that there are no significant preference differences introduced by the pandemic. The remainder of the section should be read with this in mind. The notable exceptions include: An increased ASC for bus indicating that bus is chosen more frequently relative to car and compared to the baseline. Full-time employees choose the train less frequently which could imply that the pandemic induced a slight shift in commute modes away from train to car. Train's satiation (Gamma) on the other hand increased which means that if train is chosen in a given week, its mode share tends to be considerably higher than before the pandemic. The workforce with a mixture work arrangement choose train significantly less frequently than before. Again, reduced commuting activity and a shift in commute mode could explain this. Finally, people with a GA (annual nationwide PT subscription) add a bicycle to their modal mix more frequently than before.

Considerable unobserved heterogeneity and panel effects are present at highly significant levels and across all modes except for walk (see Sigma). Mode preferences are potentially governed by a wide array of personal attributes and attitudes which can be captured by the random error component.

As elaborated in Section 2.3.3 the gamma parameter captures satiation and therefore the continuous mode share dimension. Clearly, the parameter closely matches the observed patterns, where car and train have the highest mode distance shares by a wide margin. Interestingly, train is more satiated than car which does not contradict observed patterns as gamma is conditional on having chosen the mode in a given week. I.e., if train is chosen in a given week it tends to have a considerable mode distance share. Satiation increased across all modes from the baseline to the normalization phase, which can be read as individuals using the same modes more intensively.

Switching to the discrete dimension (where car is the reference alternative) all modes except for walk depict a negative average inter-individual utility (ASC). Interestingly, these differences diminished for all modes in the normalization period, indicating that the mode share of car lost relative to the other modes.

While the PT subscriptions (GA, Halbtax and regional subscriptions) strongly predict PT usage in the baseline, they no longer do in the normalization. Potentially, a lot of the respondents cancelled these subscriptions during the pandemic (and are still labelled as possessing these subscriptions whereas in reality, they do not).

Further, in line with the discussion of Figure 2.7, there are no significant differences in mode distance shares between the working arrangements (except for a decreasing train mode share for the mixture population, as previously discussed). This is to say, that there either are none or that differences are attributed to other socioeconomic factors or unobserved heterogeneity. In other words, working arrangements could segment the population along socioeconomic variables (such as education levels) which in turn potentially have different mode share preferences. Also, modelling absolute mileage could prove more fruitful when eliciting differences between working arrangements.

In summary, individuals intensified the use of one particular mode as explained by increasing satiation parameters (however, only the difference in train satiation was significant). The car's relative importance decreased with differences in alternative specific constants (ASC) being positive. PT users cancelled their subscriptions during the pandemic. Working arrangements do not predict mode share preferences but could potentially still be an important lever as they could influence mode share preferences via differences in socioeconomic characteristics. Future research should be devoted to understanding absolute differences such as mileage. The pandemic should not be read as a structural break in mode preferences as only a few parameters were found to differ between the two observation periods. This is in stark contrast to the study by Molloy *et al.* (2021b) and Meister *et al.* (2022) who found considerable modal shifts induced by the pandemic. The findings from this work suggest that these changes were not made habitual but can be attributed to the unprecedented circumstances and constraints brought by the pandemic.

2.5 CONCLUSION AND OUTLOOK

This paper described the evolution of various mobility patterns before during and after the pandemic. The ambition was to understand modal splits and the impact of home office on transport demand beyond the COVID pandemic.

The key insights from our analysis are as follows: Both the bicycle and walking boom were temporary phenomena. In the case of bicycle, exceptionally large stage lengths during the first phase explain the boom whereas for walk, the home office population showed a pronounced peak during the first lockdown.

All PT modes were strongly depressed during the pandemic and car could temporarily expand its mode share. However, this was not a sustainable development but has normalized again. Bus could expand mode distance share and train still shows a strong upward trend across working arrangements. With decreasing uncertainty and infection risk, further recovery of PT modes can be expected.

Mode frequency shares rebounded more strongly than distance shares. This could be explained by diminished commuting activity and shorter trips. Both factors could explain the attribution of mode share to bus and bicycle as these modes are more likely to be chosen on shorter stages.

It remains unclear to what extent and along which channels hybrid work arrangements impact transport demand. While home office was an effective tool for reducing transport demand during the crisis (and with enforced lockdowns) it is questionable whether these findings translate to normal times. Hybrid work arrangements segment the population along sociodemographic attributes and these segments have different mobility patterns. The MDCEV model strengthens this hypothesis in so far as no significant preference differences can be attributed to the work arrangement attributes when controlling for sociodemographic factors (except for the mixture work and a negative coefficient for train). Hence, modeling approaches that suggest no causal effect of home office on the variable of interest should keep in mind, that the effect could be mediated over different user compositions.

While transport behavior was commented to be very different during the crisis, the pandemic should not be read as a structural break in mode preferences. This is probably also the most relevant policy implication of this paper: Changes observed during the pandemic (reduced peak traffic volumes, shifts to non-motorized forms of transport and avoidance of PT) were not made habitual. Therefore pre-pandemic challenges translate to the post-pandemic era.

The presented analysis could be strengthened by estimating a panel MMDCEV on all stages simultaneously, similar to Meister *et al.* (2022). The evolution of parameters throughout the pandemic could yield interesting insights. Further, more comprehensive post-estimation should be conducted, shifting focus on variable leverage and sensitivity rather than significance (e.g., by computing marginal probability effects). Satiation parameters could be modeled as a function of socioeconomic attributes, shedding light on different satiation profiles. Further, it is essential to develop a better understanding of the home office population to estimate the impact of new hybrid work arrangements on transport demand and beyond relative mode shares. Lastly, model building and selection are said to be an art. The field could benefit from aligning its understanding of when it is justifiable to exclude non-significant variables as well as how to comment on the (absolute) quality of a model.

3

ON THE RELATION BETWEEN RESPONSE BURDEN AND RESPONSE RATE

All models are wrong, some are useful.

— George Box

We investigate the relation between a survey's response burden and response rate, differentiating recruitment efforts and incentives paid. The results indicate that the effect of response burden is more negative than previously expected. Recruitment shifts the response curve upwards, while incentives flatten it. Surveys beyond 2'000 points appear overly burdensome, sustaining high response rates only through recruitment coupled with incentives. Without incentives, the level effect of recruitment quickly vanishes. Contrary to previous findings, we cannot identify a negative time-trend. The data, functions and workflow underlying this analysis are organized as an R-package to foster a collective effort towards understanding response rates.

This chapter is based on the following paper

Heimgartner D. and K. W. Axhausen (2024) Predicting Response Rates Once Again, *Transport Findings*.

Author contributions

Study conception and design: all authors; data processing: D. Heimgartner; analysis and interpretation of the results: D. Heimgartner; original draft: D. Heimgartner; writing, reviewing and editing: all authors. All authors reviewed and approved the final manuscript.

The following changes were made

The table containing the full data sample (originally in the Appendix) was omitted; The text elaborating on the basic workflow on Page 37 was revised.

3.1 INTRODUCTION

Counting *response burden scores* (Schmid and Axhausen, 2019) is not a very popular task at the Institute for Transport Planning and Systems (IVT, ETH Zurich). One or the other former PhD student got away without reporting them. However, the collective effort over the years yielded a unique dataset allowing us to understand response rates as a function of recruitment efforts and incentives. Other research institutes might therefore be encouraged to also contribute. This paper briefly elaborates the methodology once again and introduces the **responseRateAnalysis** R-package (Heimgartner, 2024c) with its helper functions to easily replicate the results. Since the last update (Axhausen and Schmid, 2019) a handful of students left not until the final response burden score of their surveys was counted. Thanks to them, we feel that the time is right to update response rates results once again.

The main purpose of this paper is to replicate the analysis, update the estimates based on the enlarged sample and to make the analysis easily replicable: The R-package can be installed as explained below but we hope that other research groups rather clone the repository and contribute with their scored survey instruments according to the guidelines outlined on GitHub so that we or they can predict response rates from time to time again.

```
R> devtools::install_github("dheimgartner/responseRateAnalyis")
```

3.2 METHODS

The main data collection effort consists of scoring the survey instruments according to Table 3.1.

In comparison to the previous publication (Schmid and Axhausen, 2019), 14 additional surveys have been scored and categorized by IVT members. *Recruitment* means that the respondents were contacted prior to the survey and they agreed to participate. *Incentives* mean any form of stimulus to motivate respondents to participate (usually a monetary payment upon completion of the survey). Unfortunately, the form and level of the incentive have not been recorded. A new category (no recruitment but with incentive payments) can now be distinguished. However, only five studies fall in this category. The current state of the database is attached to the package `response_rates`, documented (`?response_rates`) and can be loaded by

```
R> data("response_rates", package = "responseRateAnalysis")
```

Item	Points
Question or transition (up to 3 lines)	2.0
Each additional line	1.0
Closed yes/no answers	1.0
Simple numerical answer (e.g., year of birth)	1.0
Rating with up to 5 possibilities	2.0
Rating with more than 5 possibilties	3.0
Left, middle, right rating	2.0
Scales with 3 and more grades	2.0
Best of ranking with cards	4.0
Second and each additional best ranking	3.0
Answer to sub-questions of up to 5 words	1.0
Answer to sub-questions of up to 2 lines	2.0
a) Response to half-open question with less than 8 possibilities	2.0
Each additional one	2.0
b) Response to half-open question with at least 8 possibilities	4.0
Each additional one	3.0
Answer to "please specify"	2.0
First answer to an open question	6.0
Each additional answer to the open question	3.0
Mixing showcards	6.0
Giving/showing a card to the respondent	1.0
Per response category on a showcard	1.0
Filter	0.5
Branching	0.5
For each stated choice question with 2 alternatives	2.0
For each stated choice question with 3 alternatives	3.0
For each variable of the stated choice situation and each question	1.0

TABLE 3.1: Response burden: Points by question type and action.

The distribution of the response burden scores (RBS) for the four recruitment (R) and incentive (I) categories are visualized in Figure 3.1. The following abbreviations are used throughout the text: For example, *RxI* stands for the category where respondents were recruited as well as incentives paid. An *N* negates; hence as an example, *NRxNI* reflects the category without recruitment and without incentives (i.e., participants were not contacted prior to the survey administration and were not promised any form of incentive upon completion). The median RBS is 399 and surveys with a score higher than 1'500 are rare (twelve points roughly correspond to a one-minute response time).

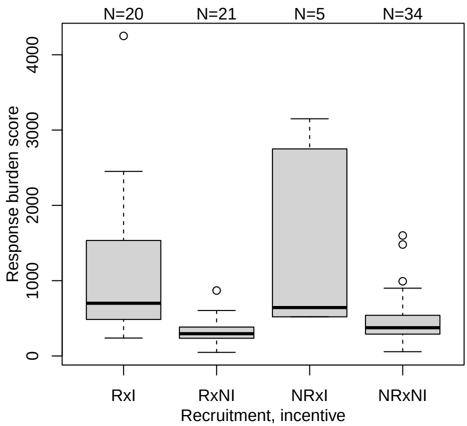


FIGURE 3.1: Distribution of the response burden scores for *recruitment x incentive* categories. *RxI* stands for recruited, with incentives, *N* negates.

Building on Axhausen and Schmid (2019), we estimate a logistic regression model relating response burden scores to log-transformed response rates

$$\log\left(\frac{y_i}{100 - y_i}\right) = \beta_0 + \beta_1 \frac{x_i}{1000} + \varepsilon_i \tag{3.1}$$

where y_i denotes the response rate (in percent), x_i represents the ex-ante response burden score, and ε_i is a normally distributed clustered error term (similar errors for different survey waves of the same study). Observations were weighted by the square root of the sample size. The model was estimated for the entire sample (excluding surveys with a sample size less than ten) as well as separately for recruitment by incentive category. The exponential $\exp(\beta_1)$ represents a marginal change in the odds ratio (i.e., participation vs. non-participation).

If a survey instrument's response burden score increases by 100 points, the odds of participating decrease according to

$$\left(\exp\left(\frac{\beta_1}{1000}\right) - 1\right) \cdot 100. \tag{3.2}$$

The basic workflow is as follows

1. `default_data()` loads and prepares the `response_rates` data for estimation. It selects the input variables, computes the weights, rescales the response burden score and log transforms the response rate.
2. Fit a linear regression model with `lm()`.
3. Add clustered standard errors with `add_clustered()()` which uses the **clubSandwich** (Pustejovsky, 2024) and **lmtest** package (Zeileis and Hothorn, 2002) under the hood to correct standard errors and related statistics.
4. The functions from the **texreg** (Leifeld, 2013) package (e.g., `screenreg()` or `texreg()`) work together with the class '`clustered`' '`lm`' (as returned by `add_clustered()`) and produce regression tables (such as the ones reported here).

The following code conducts the analysis for the full sample (i.e., same slope but different intercepts for the *recruitment x incentive* categories)

```
R> dat <- default_data() %>%
+    ## to be consistent with previous publications
+    filter(sample_size >= 10)
R> fit <- lm(y ~ 0 + x + RxI + RxNI + NRxI + NRxNI,
+    data = dat, weights = weight)
R> m1 <- add_clustered(fit, cluster = dat$survey_id, type = "CR2")
R> class(m1)
```

```
[1] "clustered" "lm"
```

We repeat the above estimation for different samples, comparing the estimates of the last publication to the updated ones as well as estimate separate models for the four different recruitment and incentive categories. Table 3.2 summarises the results.

3.3 FINDINGS

For the newly added group (no recruitment but with incentive payments, *NRxI*) the effect of the response burden is not significant, as expected because of limited sample size. Due to the logistic transformation, parameters reflect changes in log-odds when the RBS marginally increases. The effect of response burden is generally more negative than previously expected. The strongest effect can be found for the recruited subsample without incentive payment (*RxNI*), where the odds of participating decrease by -0.297 (i.e., roughly 30%) according to Equation 3.2 if the RBS increases by 100 points. The other comparisons are listed in Table 3.3.

	Updated models					Old models†			
	Pooled	RxI	RxNI	NRxI	NRxNI	Pooled	RxI	RxNI	NRxNI
Response burden	-1.01^{***}	-0.31^{**}	-2.97^{***}	-1.05	-1.63^{**}	-0.58^{**}	-0.32^{**}	-1.55	-1.25^{***}
	(0.19)	(0.11)	(0.72)	(0.40)	(0.47)	(0.17)	(0.11)	(1.16)	(0.31)
RxI	1.89^{***}					1.51^{***}			
	(0.25)					(0.20)			
RxNI	0.62					0.84^{***}			
	(0.33)					(0.15)			
NRxI	-0.73								
	(0.57)								
NRxNI	-0.64					-1.11^{***}			
	(0.34)					(0.20)			
Intercept		1.23^{***}	1.49^{***}	-0.64	-0.38		1.25^{***}	1.13^{**}	-0.81^{***}
		(0.16)	(0.26)	(0.74)	(0.41)		(0.18)	(0.32)	(0.20)
R^2	0.81	0.13	0.71	0.92	0.16	0.79	0.13	0.13	0.22
Adj. R^2	0.80	0.08	0.70	0.90	0.13	0.78	0.08	0.07	0.19
Num. obs.	79	20	20	5	34	67	19	18	30
LL	-103.96	-20.97	-15.51	-2.48	-47.70	-70.72	-20.75	-13.94	-31.10
AIC	219.93	47.94	37.02	10.97	101.39	151.45	47.49	33.89	68.20
BIC	234.15	50.92	40.00	9.80	105.97	162.47	50.33	36.56	72.40

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1; †Based on the sample of the last publication. *RxI* = Recruited, with incentives, *N* negates

Table 3.2: Logistic regression results: Regressing response burden score on (logit-transformed) response rates.

Category	Updated models [%]	Old models [%]
Pooled	-10.09	-5.79
RxI	-3.13	-3.23
RxNI	-29.66	-15.50
NRxI	-10.51	
NRxNI	-16.30	-12.46

RxI = Recruited, with incentives, *N* negates.

Table 3.3: Percentage change in the odds of participating if the response burden score increases by 100 points.

The back-transformed relationship between response burden and response rates (response rate curve) is visualized in Figure 3.2, along their confidence intervals (i.e., the shaded area reflects the uncertainty of the curve estimates and is not a prediction interval). Recruitment shifts the curve, while incentives flatten it. Notably, the domain above a response burden score of 2'000 is sparsely populated, and the few observations potentially strongly influence the curve's shape (however, according to *Cook's distance* no influential outliers are present in our data). The results indicate that surveys beyond 2'000 points appear overly burdensome for respondents, sustaining high response rates only through recruitment efforts combined with incentive payments, intensive care of the respondents and general interest of the respondents in the topic of these intense studies.

Generally, the 14 new data points do not dramatically change the overall shape of the curves (Figure 3.2, RHS), but the curves are slightly steeper as explained based on the parameter estimates. *RxI* is almost identical (only two new data points were added). For *NRxNI* the confidence bounds increased because two of the five added surveys have unprecedented high response rates. For the category *RxNI* the function has gained support for higher response burdens which substantially steepened the curve and reduced its uncertainty. In particular, we now have higher confidence that the curve quickly joins the other response curves on the domain above 1'500 response burden points. I.e., recruitment without incentive payments only matters for surveys with low response burden (but can make a big difference there).

Similar to Schmid and Axhausen (2019), we can add a linear time-trend with the year 2004 (when the survey scoring effort started) serving as the

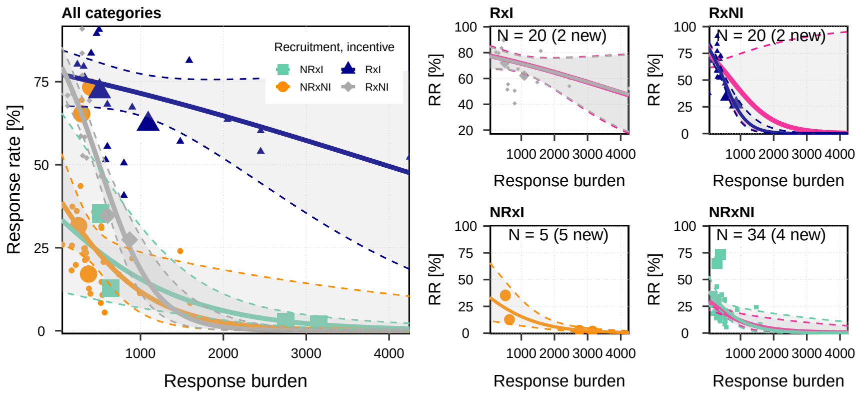


FIGURE 3.2: Response rate curves (response rates as a function of the response burden). The left-hand panel compares the curves for each *recruitment x incentive* category based on the four separately estimated models (*RxI* stands for recruited, with incentives, *N* negates). The right-hand (smaller) panels compare the response rate curves to the ones based on the data of the previous publication (pink lines). New data points (since the last publication) are enlarged.

base. The following code shows the trivial addition of the time-trend to the pooled model.

```
R> dat$year <- dat$year - 2004
R> fit_t <- lm(y ~ 0 + x + RxI + RxNI + NRxI + NRxNI + year,
+    data = dat, weights = weight)
R> mt <- add_clustered(fit_t, cluster = dat$survey_id, type = "CR2")
```

We repeat the steps for the individual categories and synthesise the results in Table 3.4. In contrast to Schmid and Axhausen (2019) we do not find a negative time-trend and therefore do not support the hypothesis of a general fatigue and less willingness to participate in our surveys.

	No time-trend					With time-trend				
	Pooled	RxI	RxNI	NRxI	NRxNI	Pooled	RxI	RxNI	NRxI	NRxNI
Response burden	-1.01^{***}	-0.31^{**}	-2.97^{***}	-1.05	-1.63^{**}	-1.02^{***}	-0.33^{*}	-3.28^{**}	-1.41^{*}	-1.50^{**}
	(0.19)	(0.11)	(0.72)	(0.40)	(0.47)	(0.20)	(0.13)	(0.85)	(0.24)	(0.44)
RxI	1.89^{***}					1.82^{***}				
	(0.25)					(0.26)				
RxNI	0.62					0.55				
	(0.33)					(0.46)				
NRxI	-0.73					-0.86				
	(0.57)					(0.58)				
NRxNI	-0.64					-0.72^{**}				
	(0.34)					(0.24)				
Intercept		1.23^{***}	1.49^{***}	-0.64	-0.38		1.06^{*}	1.49^{***}	-12.31	-0.71^{*}
		(0.16)	(0.26)	(0.74)	(0.41)		(0.43)	(0.32)	(8.03)	(0.34)
Time-trend						0.01	0.02	0.01	0.68	0.03
						(0.02)	(0.05)	(0.06)	(0.46)	(0.05)
R^2	0.81	0.13	0.71	0.92	0.16	0.81	0.14	0.72	0.97	0.20
Adj. R^2	0.80	0.08	0.70	0.90	0.13	0.80	0.04	0.68	0.95	0.14
Num. obs.	79	20	20	5	34	79	20	20	5	34
LL	-103.96	-20.97	-15.51	-2.48	-47.70	-103.83	-20.81	-15.38	0.06	-46.95
AIC	219.93	47.94	37.02	10.97	101.39	221.65	49.61	38.76	7.89	101.89
BIC	234.15	50.92	40.00	9.80	105.97	238.24	53.59	42.74	6.33	108.00

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1; *RxI* = Recruited, with incentives, *N* negates.

Table 3.4: Logistic regression results: Adding a linear time-trend

4

DATA

I dream my painting and I paint my dream.
— Vincent van Gogh

The Swiss New Normal is defined by a substantial increase in telework adoption following the COVID-19 pandemic. Although telework has been extensively studied in the transport literature since the start of the ICT revolution, previous findings may not be applicable to the current context due to evolving economic conditions, personal preferences, and employer perspectives. The net benefits of telework for energy consumption and its climate impact remain ambiguous, as the potential higher-order effects that might offset energy savings from reduced commuting are still under debate. Our survey is designed to model the options, adoption, and frequency of telework. We conducted two stated preference experiments: The first examines preferences for various hybrid work arrangements and the influence of work policies on telework adoption, while the second explores the relationship between telework frequency and mobility tool ownership, a previously neglected higher-order effect. This paper focuses on data collection methods, analyzes response behavior, and provides a descriptive overview of the telework landscape in Switzerland. Our data suggests that the pandemic has increased the telework share in Switzerland by 15 percentage points. Of the population, 60% hold teleworkable jobs, and 91.33% of these individuals wish to utilize telework. However, a gap of 20 percentage points exists between those who can work from home and those who actually do. Additionally, about one-quarter of teleworkers desire to telework more frequently but are restricted from doing so. Telework patterns also vary throughout the week, with Fridays being the most popular day for working from home, suggesting significant variations in transport network loads. We found no evidence that telework negatively impacts emissions through a shift from public transport (PT) subscriptions to car ownership. Teleworkers tend to cancel PT subscriptions and purchase half-fare cards, but this behavior occurs only at high telework frequencies (4+ days per week). Nonetheless, this shift could have second-order effects at the trip level: households with cars and no PT subscriptions may prefer car travel over other modes of transport. The reference manual can be found in Appendix A.3.3.

This chapter is based on the following paper	Heimgartner D. and K. W. Axhausen (2024) Multimodality in the Swiss New Normal: Data Collection Methods and Response Behavior in a Multi-Stage Survey with Linked Stated Preference Designs, *Transportation*, under review.
Author contributions	Study conception and design: all authors; survey design: all authors; data collection: D. Heimgartner; analysis and interpretation of results: D. Heimgartner; original draft; D. Heimgartner; writing, reviewing and editing: all authors. All authors reviewed and approved the final manuscript.
The following changes were made	The section elaborating on the response rate analysis was shortened, as it largely overlaps with Chapter 3; Figure 4.9 was improved and now shows the individual bootstrap predictions; The wording of the SPs introductory text was incorporated in the chapter (instead the Appendix); The remainder of the Appendix was omitted.

4.1 INTRODUCTION AND MOTIVATION

The revolution in information and communication technologies (ICTs) enabled remote work, sparking interest in the relationship between telework, transport demand, energy, and climate impacts (Salomon, 1986; Hook *et al.*, 2020). Alongside economic and digital transformations, the service industry's growth has also contributed to the steady increase in telework. However, the COVID-19 pandemic dramatically accelerated this trend, quadrupling the home office share in a few quarters (Barrero *et al.*, 2023). It remains uncertain how pre-pandemic findings translate to the post-pandemic "new normal". For instance, Asmussen *et al.* (2023) suggests a reduction in the heterogeneity of telework adoption and frequency, with fewer sociodemographic and work-related variables influencing these factors. Additionally, the literature shows significant variation in home office potential and adoption across countries, cities, and economic sectors (see Dingel and Neiman, 2020; Groen *et al.*, 2018; Cetrulo *et al.*, 2020), complicating the generalization of findings.

Before the pandemic, working from home was rare and often stigmatized, seen as detrimental to career advancement, which discouraged workers from expressing their desire to telework (Brewer and Hensher, 2020). Indeed, Mokhtarian and Salomon (1996) found that telework was a "preferred impossible" option for many workers. The pandemic, however, helped break this stigma and relaxed some constraints, making telework a "preferred possible" scenario for many.

Hybrid work policies can benefit employees and employers by responding to employee demands, reducing labor costs, expanding the labor pool, lowering office space expenditures, and complying with environmental mandates (see Nilles, 1988; Olson, 1989; Bernardino, 1995). Therefore, it should be acknowledged that observed telework frequencies are the outcome of a negotiation process between employers and employees (i.e., the classical demand and supply side in labor markets).

Despite significant interest in telework research, data sources tailored to understanding its complexities are rare and often limited to national or regional census data, which provide sparse telework-related information. These existing data sources struggle to disentangle the reasons behind an individual's telework habits, such as personal preferences, job-related factors, and employer constraints. Our data collection aims to fill this gap for Switzerland, providing a rich dataset to support various telework-related research questions. Thus, the primary motivation for this paper is to detail the survey methods and collected data.

The choice to telework depends not only on individual characteristics and attitudes but also on work arrangement characteristics. Despite the recognized need for this, little work has explored telework adoption and frequency choices under different work arrangements. Bernardino *et al.* (1993) investigated choices involving telecommuting frequency, schedule flexibility, salary, available equipment, and cost responsibilities, concluding that incurring costs is more acceptable than a salary decrease. Furthermore, an asymmetry exists between salary increases and decreases, where a decrease hinders adoption more than an increase encourages it, consistent with prospect theory (Kahneman and Tversky, 1979). In contrast, Sullivan *et al.* (1993) focused exclusively on cost implications without examining other factors like schedule flexibility. Appel-Meulenbroek *et al.* (2022) studied workplace location preferences, finding that workplace attractiveness can influence telework decisions, with factors such as crowdedness and noise being significant. This paper expands on this research by implementing a work arrangement stated preference (SP) experiment, where participants select their preferred work arrangement and intended telework frequency, based on attributes and levels defined through a pre-study.

Literature on the energy and climate impacts of teleworking highlights the importance of indirect channels that might offset reduced commuting, including changes in non-work travel and home energy consumption (Hook *et al.*, 2020). Significant lifestyle changes might bring about higher-order effects (Horner *et al.*, 2016) such as relocation (de Vos *et al.*, 2018) or re-evaluation of mobility tool ownership. In Switzerland, public transport (PT) is a primary commuting mode, with subscriptions like the national season ticket (GA) being popular. Previous studies suggest that in countries where PT is common, teleworking has less impact on energy use compared to countries dominated by private car use (Mokhtarian, 2009; van Lier *et al.*, 2014). However, reduced PT commutes might lead individuals to reconsider PT subscriptions and potentially shift to less sustainable modes such as cars. Mobility tool ownership significantly influences mode choice (Schmid *et al.*, 2023) and thus the transport equilibrium. Telework could make car ownership more attractive by enabling greater use of the household car by other members on home office days (Hook *et al.*, 2020). Wang and Mokhtarian (2024) calls for further exploration of the relationship between telework and vehicle ownership. This paper addresses this by investigating the higher-order effect of telework on mobility tool ownership, using a second SP experiment to examine the relationship between work from home (WFH) frequency and mobility tool ownership (car, car sharing, bike, E-bike, and various PT subscriptions).

Experimental approaches to mobility tool ownership are rare due to the high complexity of attribute combinations, making it difficult to construct realistic choice sets. One approach to address this is the stated adaptation design (e.g., Schmid *et al.*, 2019; Erath and Axhausen, 2010). Alternatively, some studies reduce the choice task, focusing on trade-offs between car and annual season ticket ownership (e.g., Weis *et al.*, 2010; Scott and Axhausen, 2006) or considering a single mobility tool (e.g., Fang, 2008; Jong *et al.*, 2004; Hess *et al.*, 2012).

This study focuses on the German-speaking part of Switzerland, particularly the city and canton of Zurich. Switzerland is an ideal study area due to its high proportion of white-collar workers and diverse mobility tool ownership. Zurich, a financial hub, has experienced significant changes due to the pandemic. Prior to the pandemic, data security and privacy concerns limited home office possibilities, which have now become feasible.

A total of 10'441 individuals from the Federal Statistical Office's sampling frame were contacted, with 3'234 completing the first survey. Among these, 1'280 telework-eligible individuals were invited to participate in the two SP experiments, with 922 completing all stages, resulting in a high-quality representation of the population and a comprehensive set of SP choices.

The data collected in this work allows researchers to investigate key questions: Who can, may, and wants to telework? What are the preferences for hybrid work arrangement characteristics, and how do they affect telework adoption and frequency? How do teleworkers adjust their mobility tools in light of hybrid work arrangements? This study aims to develop a detailed understanding of WFH and its relation to mobility tool ownership. Further, Mokhtarian and Salomon (1994) emphasized the need to differentiate between possibility, preference, and choice, noting that possibility is constrained by factors such as job suitability and managerial approval. Our dataset includes item batteries to control for this home office feasibility.

The broader goal of this data collection was to enrich a synthetic population for MATSim (Horni *et al.*, 2016) and simulate transport demand implications. Results are reported in Heimgartner *et al.* (2024b).

The remainder of the text is structured as follows: Section 4.2 details the survey methods and SP experiments. Section 4.3 analyzes response behavior and relates the response rate to the response burden score as proposed by Axhausen *et al.* (2015). Section 4.4 presents a descriptive analysis addressing who can, may, and wants to work from home. Section 4.5 demonstrates the usefulness of the data by investigating telework treatment effects on mobility tool ownership. Finally, Section 4.6 concludes the study.

4.2 SURVEY METHODS

The following sections provide an in-depth explanation of the survey instruments' structure and the details of the stated preference (SP) designs. Two different population samples from the German-speaking part of Switzerland were recruited for the two main survey waves: the pre-study and the main study. For the pre-study, 7'967 addresses were purchased from an address dealer, targeting age and gender marginals from the mobility and transport microcensus (MTMC21, ARE and BFS, 2024). For the main study, a stratified sample of 10'441 individuals was obtained from the Federal Statistical Office. Respondents from the canton of Zurich were over-sampled due to the city's and canton's partnership in this project. Additionally, the data collection aimed to estimate statistical models for MATSim, with scenario analysis planned for that particular area.

Both samples were invited by postal letter to participate in the introductory survey. One reminder was sent, and for the main study, an incentive of 20 Swiss francs was offered upon completion of all three stages of the study. After completion of the introductory survey, communication happened via E-mail. The importance of participating was emphasized, even if the respondent's current work situation did not permit telework. Key statistics of the four survey instruments are detailed in Table 4.1.

	Survey			
	Pre-study	Intro	WFH-SP	MTO-SP
Start	2022-05-11	2023-06-02	2023-06-23	2023-07-07
End	2022-06-13	2023-08-28	2023-09-11	2023-09-10
Questions [N]	77	69	17	21
Invited [N]	7967	10441	1280	1067
Completed [N]	1345	3234	1067	922
Completed [%]	16.9	31.0	83.4	86.4
Median response time [min]	24.2	13.0	6.5	6.1
Response burden score*	373	254	88	163

*Response burden scores are based on Axhausen *et al.* (2015)

Table 4.1: Surveys key statistics.

4.2.1 *Pre-study*

As only little academic work has investigated the importance of work arrangement attributes on telework adoption, the main purpose of the pre-study was to identify attributes of relevance in the decision-making process required to design meaningful trade-offs in the SP. Participants were asked to rank order a menu of eight proposed generic work arrangement attributes (e.g., flexible working hours, free choice of home office days, financial compensation, etc.) and subsequently distribute 100 points among their top four choices. We find that employees place high value on efforts to maintain collegiality, corporate identity, and flexibility. Flexibility in choosing when to telework (day of the week), where to work from, and time management when teleworking. Meanwhile, financial incentives are of less relevance. The reader can later confirm in Section 4.2.3 that we accounted for this revealed attribute importance in the SP design.

4.2.2 *Stage I: Introductory survey*

At the first stage, respondents were invited to participate in an online survey that collected socio-economic information, household structure, current home office status, work and residential situation, as well as mobility behavior and mobility tool ownership. Only individuals currently in the workforce qualified for participation, and telework-related questions were asked exclusively to those with jobs suitable for remote work.

A series of Likert-scale questions was included to assess an individual's theoretical telework feasibility (*teleworkability*). These questions encompassed job characteristics, the residential environment, and personality traits. This distinction allows modelers to differentiate between possibility and preference, an important concept emphasized by Mokhtarian and Salomon (1994). A factor analysis was conducted on these items and two factors emerged as important: One representing job-related dimensions (work context and work activities), and the other relating to personal characteristics and the home office environment. These latent factors could be incorporated into modeling approaches, either directly or indirectly, such as through a probabilistic choice set formation approach as in Manski's model (e.g., Manski, 1977; Bierlaire *et al.*, 2010).

4.2.3 *Stage II: Work from home SP*

Individuals identified as eligible for telework were invited to participate in the second stage – the work from home (WFH) SP. Eligibility required participants to be in the workforce and to have a work profile permitting at least one home office day per week, regardless of whether their current employer offers this option. Self-employed individuals were excluded since they do not face exogenous work arrangements.

The selection of attributes was largely inspired by Bernardino (1995) and insights from the pre-study detailed in Section 4.2.1. Salary adjustments were included in the design despite being deemed irrelevant by participants in the pre-study. This inclusion was justified for three reasons: First, salary adjustments as (dis)incentives for home office have been a topic of recent public debate; second, this attribute serves as a natural cost component, allowing modelers to interpret other attributes in a monetary (willingness to pay) framework; third, the attribute was found to be relevant in Bernardino (1995).

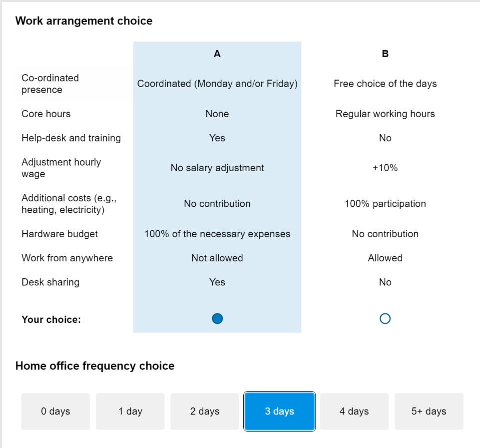
Attributes and their levels are presented in Table 4.2. Notably, three attributes (*hardware budget*, *additional cost*, and *salary adjustments*) imply a cost component and a marginal utility of one Swiss franc. It is to be tested whether the monetary utility equivalent remains constant across these three attributes. The *coordination* attribute could have both positive and negative utility implications: While it reduces personal flexibility, it also coordinates office attendance, enhancing collaboration and collegiality. The *desk sharing* attribute captures the concept of flexible office space utilization and expands on Appel-Meulenbroek *et al.* (2022) where work location attributes such as *noise, openness* and *crowdedness* were tested and found to be important. The *help and training* attribute implies support for technical difficulties and training, promoting effective digital collaboration and a successful home office culture. The full factorial design was reduced according to D-efficiency principles. Each participant completed four choice tasks.

Bernardino (1995) included telecommuting frequency as an attribute of the work arrangement, potentially resulting in unrealistic levels that do not account for teleworkability. In contrast, we propose a sequential choice setting where respondents first choose their desired work arrangement and subsequently reveal their preferred frequency, given the characteristics of the selected arrangement. However, this approach may result in unbalanced attribute-level combinations in the frequency choice, as less attractive work arrangement features are filtered out in the initial choice (see the discussion in Figure 4.4). Further, it might necessitate a simultaneous modeling approach since work arrangement attributes are no longer exogenous in the frequency choice. The introductory text explaining the WFH choice task was as follows

Attribute	Level	Remark
Coordinated presence	Mon/Fri Tue/Wed/Thu	Office attendance of team members is coordinated on these days.
Core hours	None Regular working hours	Employee can freely allocate working time or is expected to work during regular working hours.
Help-desk and training	Yes No	Help desk for technical assistance and training for effective home office collaboration and management.
Salary adjustment	-10% No salary adjustment +10%	On an hourly wage basis for home office hours.
Additional cost	No contribution 50% 100%	Compensation for increased energy consumption among others.
Hardware budget	No contribution 50% of the necessary expenses 100% of the necessary expenses	Yearly budget for setting up a productive home office work station.
Work from anywhere	Allowed Not allowed	Only within Switzerland.
Desk sharing	Yes No	Restructuring of the office space.

Table 4.2: Attributes and levels of the WFH-SP experiment.

On the following pages, you are asked to choose between different **work arrangements** and tell us about **how many days** you would work from home under the selected scenario. Here is what a choice situation looks like



Work arrangement choice

	A	B
Co-ordinated presence	Coordinated (Monday and/or Friday)	Free choice of the days
Core hours	None	Regular working hours
Help-desk and training	Yes	No
Adjustment hourly wage	No salary adjustment	+10%
Additional costs (e.g., heating, electricity)	No contribution	100% participation
Hardware budget	100% of the necessary expenses	No contribution
Work from anywhere	Not allowed	Allowed
Desk sharing	Yes	No
Your choice:	●	○

Home office frequency choice

0 days | 1 day | 2 days | 3 days | 4 days | 5+ days

1. Two work arrangements are presented (A and B), which differ along eight dimensions.
2. You are asked to choose your preferred arrangement.
3. As a last step, you are asked to reveal how many days you would work from home given your selected arrangement.
4. The above choice would imply that you would prefer work arrangement A over B and would like to work from home on 3 days a week given the conditions in arrangement A.

4.2.4 *Stage III: Mobility tool ownership SP*

Conducting an SP experiment on mobility tool ownership presents challenges due to the necessity to precisely define the characteristics of each proposed mobility tool. Moreover, households may own and share multiple tools of the same type, and interdependencies between tools could exist (e.g., negative correlation between car ownership and public transport subscriptions). Therefore, decision-making involves complex trade-offs that may consider collective household preferences, bargaining dynamics, and the composition of bundles rather than evaluating each mobility tool in isolation. Accordingly, the SP design should incorporate bundled choices to assess the specific attributes of one tool against the entire set of available tools.

The bundle structure involves two primary dimensions: The availability of each considered mobility tool and their respective characteristics. Our study includes five distinct tools: cars, public transport (PT) subscriptions (national or regional season tickets), half-fare card (HT, allowing travelers to purchase PT tickets for half the price), car-sharing subscriptions, and (E-)bikes, following Becker *et al.* (2017) with additions of (E-)bikes and HT. Participants can combine these tools into 32 unique bundles (2^5 combinations), differing only in tool availability without imposing trade-offs within the same tool category (e.g., choosing between different types of cars).

Given the impracticality of directly comparing 32 alternatives (known as the "curse of dimensionality"), we initially explored an unlabeled approach in a pre-test where respondents chose between two predefined bundles. However, participants found this method too abstract and detached from their actual preferences, leading us to adopt a simpler design. In this revised approach, participants are presented with individual options for each mobility tool and are asked to compose a bundle from these options. The introductory text explaining the mobility tool ownership (MTO) choice task was as follows

In this survey, we want to determine how far **home office** impacts your **mobility tool ownership** choices. On the following pages, you are asked to choose between different mobility tools under various home office scenarios. Imagine that all your current mobility tools have expired and need to be **renewed** anyways. This is what a choice task looks like

Home office situation		
You work from home on	0 days	
Work from anywhere is		
Car		
Car type	SUV	
Fuel type	Hybrid	
Fixed cost (annual)	9411 CHF/a	
Per km cost	1.1 CHF/km	☐
PT subscription		
Subscription type	GA	
Class	2	
Fixed cost (annual)	5018 CHF/a	
Cost for additional zone		☑
Half-fare card		
Fixed cost (annual)	240 CHF/a	☐
Car sharing		
Free floating	No	
Membership fee (monthly)	15 CHF/month	
Time tariff	2 CHF/h	
Per km cost	0.8 CHF/km	☑
Bicycle		
Bicycle type	Regular bike	
Fixed cost (annual)	260 CHF/a	☐

1. In the blue box, a hypothetical home office situation is presented. The scenario consists of **how many days a week you work from home** and whether or not **working from anywhere (within Switzerland)** is allowed. The home office frequency is based on your answers from the previous survey.
2. Please take a moment to reflect on what your life and mobility behaviour would look like, **given the home office situation** presented.
3. Each choice card contains a **car** offer, a **public transport (PT) subscription** offer (either GA or regional season ticket), the price of the **half-fare card**, a **car sharing** service as well as a **bicycle** (either regular or E-bike) offer.
4. Last, you can choose for each of the five mobility tools whether or not you would like to own the tool at the conditions outlined. There are no other options available. F.ex. if you do not want to own the presented car, you don't have any other car available. So think about what composition of mobility tools would best match your needs given the home office scenario.
5. Apart from the costs presented, you can assume that **all other prices are as of today** (e.g., fuel prices, single-fare train tickets, electricity prices, etc.).
6. The above choice would imply that given the home office situation presented, you would choose to own the PT subscription and the bicycle.

While conceptually simpler, this design emphasizes the availability trade-off and explicitly abstracts from trade-offs between mobility tools of the same type (not choosing the depicted car implies not owning a car at all). Thus, a particular mobility tool is chosen if the net benefit/utility is positive. For instance, even if a participant strongly dislikes a specific car attribute (e.g., car type being luxury or sports car), they might still choose it if the disutility of not owning any car outweighs their aversion to that attribute. This approach questions whether the utility or disutility of not owning a car remains constant across choice occasions, influenced by the characteristics of other mobility tools available which should be accounted for when modeling the choices collectively.

The attributes and assumed reference values are detailed in Table 4.3 based on which a random design was generated. The cost implications of owning and using a car were meticulously considered to provide a comparable basis for trade-offs with other mobility tools. Fixed costs, depreciation, taxes, insurance, and other expenses were factored into the analysis, with data sourced from the Swiss Touring Club (2024) website for various vehicle classes and fuel types. See also the **tcsscraper** Python-package available at `https://github.com/dheimgartner/tcsscraper` providing an API to retrieve many variables for the current Swiss car fleet.

Attribute	Level	Reference	Remark
Car			
Type	Small car		
	Medium to large car		
	Minivan or van		
	SUV		
	Luxury or sports car		
Fuel	Gasoline		
	Diesel		
	Electric		
	Hybrid		
	Plug-in hybrid		
Fixed cost	0.7 (-30%)	Inferred from archetype*	Fixed costs include amortization, garaging costs, insurance, and taxes. The price of the car is reflected in the fixed cost (amortization).
	1		
	1.3 (+30%)		

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Table 4.3 – *Continued from previous page*

Attribute	Level	Reference	Remark
Variable cost	0.7 (-30%) 1 1.3 (+30%)	Inferred from archetype*	Per kilometer cost, including depreciation of the car's value, fuel or energy costs, tire costs and maintenance.
Public transport			
Type	National ST (GA) Regional ST Half-fare		
Class	First Second		Cost multiplier of 1.7 for first class
Fixed cost	0.7 (-30%) 1 1.3 (+30%)	3860 CHF/year (GA) 782 CHF/year (Regional) 185 CHF/year (Half-fare)	
Additional zone	0.7 (-30%) 1 1.3 (+30%)	40 CHF for additional zone	Only for regional season ticket
Bicycle			
Type	Regular bike E-bike (up to 25 km/h) E-bike (up to 45 km/h)		
Fixed cost	0.7 (-30%) 1 1.3 (+30%)	200 CHF/year (regular) 600 CHF/year (25 km/h) 100 CHF/year (45 km/h)	Fixed costs include amortization, maintenance, and insurance. The price of the bicycle is reflected in the fixed cost (amortization).
Car sharing			
Free-floating	Yes No		Whether or not the car sharing is station-based or free-floating.
Membership fee	10 CHF/month 15 CHF/month 20 CHF/month		
Time tariff	2 CHF/h 3 CHF/h 4 CHF/h		
Km tariff	0.8 CHF/km 1 CHF/km 1.2 CHF/km		
Scenario variables			

Continued on next page

Table 4.3 – *Continued from previous page*

Attribute	Level	Reference	Remark
Work from home	0-5+ days	Individual-specific	Either the current WFH frequency, the maximum feasible frequency (as asked in the introductory survey), the free-choice, or the observed choices in the SP.
Work from anywhere	Allowed Not allowed		

*An archetype has the average car specifics for a certain car and fuel type combination; ST = Season ticket

TABLE 4.3: Attributes and levels of the MTO-SP experiment.

4.3 RESPONSE BEHAVIOR

This section examines the demographic composition of survey participants, relates the surveys' response burdens to other studies conducted at the institute (see Chapter 3), and explores the variability in choices observed in the two SP experiments.

As previously mentioned, the survey instrument in stage I targeted the entire working population, while SP experiments focused exclusively on those eligible for telework. The distribution across cantons, completion rates, and response rates for stage I are depicted in Figure 4.1. To emphasize variability among cantons, Zurich, which was oversampled, is excluded from the linear color scale of the first two panels. The remaining German-speaking cantons are included, with invited participants proportionally reflecting their respective populations. Response rates vary across cantons, ranging from 14.29% (Glarus) to 34.10% (Lucerne).

		%		
Variable	Value	MTMC21	Pre-study	Main study
Age	18-35	29.4	17.1	27.9
	36-50	36.1	25.7	40.9
	51-65	30.9	56.6	30.5
	65+	3.5	0.7	0.8

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Table 4.4 – *Continued from previous page*

Variable	Value	MTMC21	Pre-study	Main study
Sex	Male	52.7	59.1	52.3
	Female	47.3	40.9	47.7
Married	Yes	50.5	-	50.6
	No	49.5	-	49.4
Nationality	Swiss	75.0	96.2	80.2
	Other	25.0	3.8	19.8
Education	Low	7.2	1.0	4.6
	Medium	45.2	49.7	45.6
	High	47.6	49.3	49.8
Household Size	1	18.8	12.6	16.9
	2	33.7	31.8	35.1
	3	18.6	17.9	17.6
	4+	28.9	37.6	30.4
Household Income	Not reported	15.4	5.4	6.2
	<4'000 CHF	5.5	2.9	4.4
	4'001-8'000 CHF	27.7	21.9	23.0
	8'001-12'000 CHF	26.6	37.2	28.7
	>12'000 CHF	24.7	32.6	37.7
Employment	Full time	60.6	59.8	60.6
	Part time	39.4	40.2	39.4
Telework	0	56.6	51.5	52.3
	1	14.3	17.9	15.0
	2	5.9	12.9	13.2
	3	6.5	7.6	9.9
	4	4.3	4.5	5.7
	5+	12.5	5.5	3.9
	Human Health	15.5	-	2.9
	Manufacturing	14.6	-	15.2
	Wholesale and Retail	11.2	-	9.9
	Education	8.0	-	4.5

Continued on next page

Noga Sector

Table 4.4 – *Continued from previous page*

Variable	Value	MTMC21	Pre-study	Main study
	Professionals	9.0	-	9.8
	Other	41.7	-	57.7
Mobility Tools	Car	85.1	88.4	68.2
	Car sharing	6.0	10.8	2.8
	Bike	82.2	82.6	54.6
Season Tickets	National season ticket	9.5	12.5	11.3
	Half-fare card	40.4	63.2	61.3
	Regional season ticket	11.6	8.0	17.3
	None of above	42.8	21.9	21.6

TABLE 4.4: Descriptive statistics: MTMC21 versus pre-study and main samples.

Table 4.4 presents marginal distributions of shared variables for the MTMC21 sample, the pre-study, and the main study populations. The main study sample closely mirrors the MTMC21 sample with some exceptions, likely attributable to Zurich's oversampling. Overrepresentation is noted among high-income households and PT season-ticket holders. Regarding ownership of mobility tools, comparability of marginals is limited due to differing survey questions: MTMC21 assessed access to tools while ours inquired about ownership and regular usage. Marginal distributions across reported NOGA sectors diverge notably, reflecting Zurich's status as a financial and ICT hub. Disparities in telework distributions are expected, influenced by the ongoing COVID-19 pandemic during the MTMC21 and pre-study survey periods, detailed further in Section 4.4.

Despite successful sampling, a re-weighting scheme was implemented to enhance sample representativeness. Using iterative proportional fitting, weights were adjusted based on specified variables, excluding telework and mobility tool ownership due to aforementioned limited comparability. These weights were applied to aggregate statistics whenever findings were generalized to the entire population, employing the **anesrake** R-package (Pasek, 2018) for weight determination.

Figure 4.2 shows the relationship between response burden and response rates, alongside 95% confidence intervals. The surveys of this study have enlarged symbols. Response rates closely approximate ex-ante predictions,

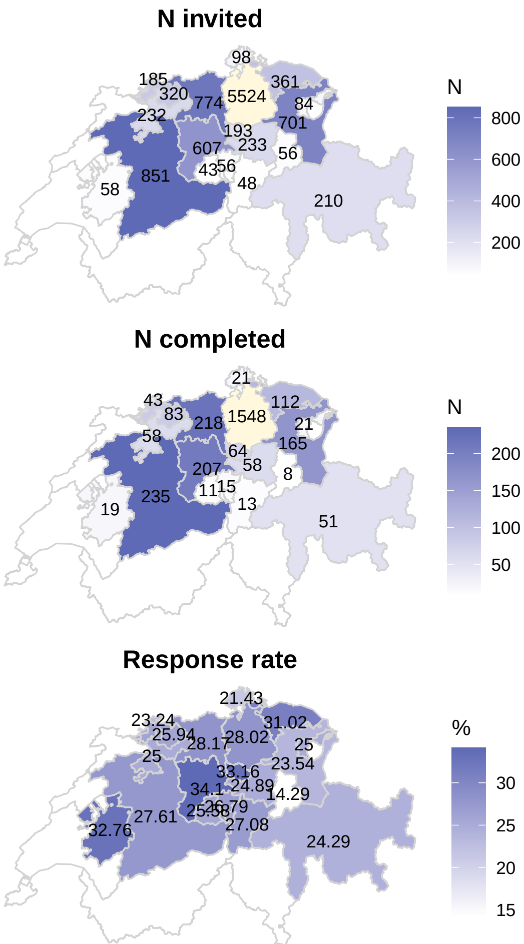

FIGURE 4.1: Distribution of invited participants, survey completion, and response rates across cantons. Zurich is excluded from the color scale in the first two panels to highlight variation among other cantons.

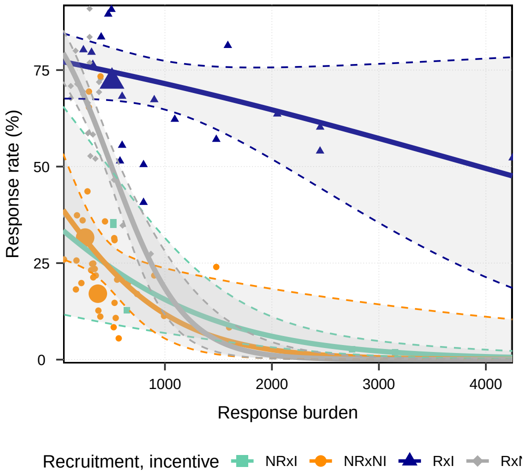

FIGURE 4.2: Relationship between response burden score and response rates. The surveys of this study are enlarged.

with the exception of the pre-study, falling below the 95% confidence bound. A potential explanation could be fatigue among respondents sourced via an address dealer, possibly due to frequent solicitations. Addresses for the main study were sourced from the Federal Statistical Office's official sampling frame, with careful measures to avoid repeated sampling. Additionally, initial participation was likely influenced by potential incentives offered upon completion of all three survey stages.

The variability in telework choices within the SP experiment is illustrated in Figure 4.3. Frequencies of telework choices reflect typical experimental work arrangement conditions but may not generalize universally. Choices of two to three teleworking days per week dominate, each accounting for over 30% of choices. Moreover, aggregate SP telework supply closely matches free-choice telework supply (Δ = -0.22 days/week), with stated frequencies differing only marginally from free-choice frequencies in most instances. This suggests that the average pre-selected telework arrangement offers limited incentives for deviation beyond the marginal day.

Given respondents first selected preferred telework arrangements before specifying intended frequencies, the extent to which attribute-level balance is sustained in the frequency choices is questioned. Figure 4.4 features separate panels for each attribute level, detailing mean telework frequencies

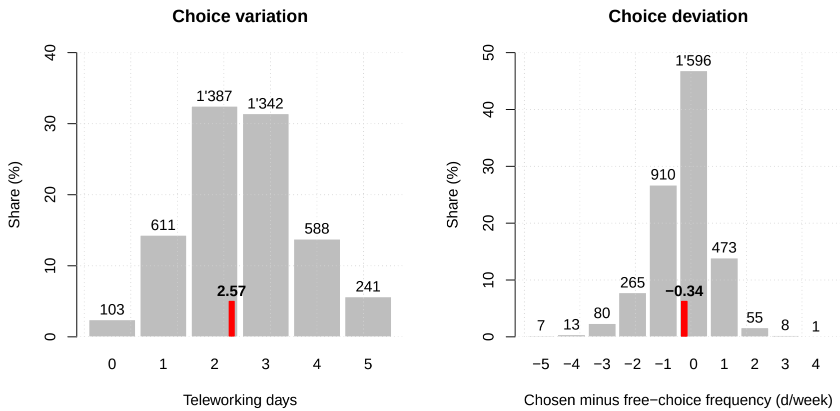

FIGURE 4.3: Variation in telework choices and deviation from the free-choice scenario.

on the left y-axis and frequency of attribute levels retained on the right y-axis. Attributes display generally balanced distributions, even in secondary frequency choices. Initial work arrangement choices filtered out some attributes such as salary decreases and restricted telework locations (*work from anywhere*). The direction of the effects (blue lines) align with intuition: Attributes favorable to telework (e.g., salary increases) correlate with increased mean telework frequencies. The reported maximum difference (*Max diff*) in each panel serves as an indicator for effect strength, highlighting salary adjustments and flexible telework locations as influential levers in telework behavior.

Figure 4.5 illustrates discrepancies between real-world and SP-implied shares of mobility tool ownership. Notably, car ownership is underrepresented, while PT subscriptions are overrepresented, reflecting the abstract nature of choice tasks. For example, one of the car attributes might be so unfavorable that respondents switch to PT, whereas in reality, they would simply buy another car. However, as these trade-offs are random they are in particular not correlated with telework frequencies and therefore should not bias telework treatment effects (see Section 4.5).

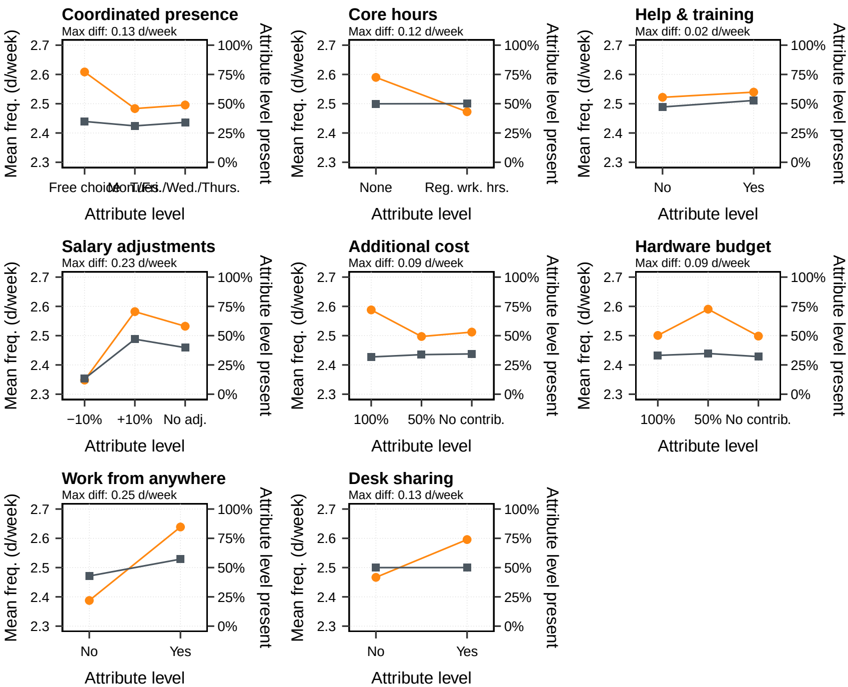

FIGURE 4.4: Relation between attribute levels and aggregate telework supply (blue lines, left y-axis) and attribute level balance (orange lines, right y-axis).

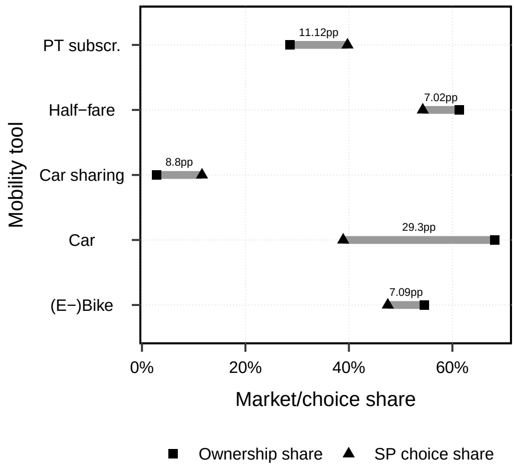

FIGURE 4.5: Comparison of real-world mobility tool ownership shares and SP choice shares.

4.4 DESCRIPTIVE FINDINGS

Our dataset offers a unique opportunity to analyze shifts in telework patterns prompted by the COVID-19 pandemic. We distinguish between individuals who have the capability (*can*), permission (*may*), and inclination (*want*) to telework, and assess the extent of untapped telework potential. Table 4.5 provides comprehensive insights into these dimensions of telework and their distribution, presenting all possible two-way contingency tables for frequency and binary indicators.

Table (12) (first row, second column of Table 4.5) reveals a profound telework potential among the Swiss workforce, with over 60% holding teleworkable positions. Of these, 91.33% express a desire to telework, indicating widespread preference for remote work. As of the survey period (June-August 2023), approximately 40% actually teleworked, which implies a 20 percentage point gap between those who can and those who do.

We now turn to telework frequency shares before, during, and after the pandemic (table indexed (11)). The lockdown period witnessed exceptional telework uptake, with over half of the workforce shifting to remote work, and about one third fully remote. Comparison with the *Feasible* scenario suggests an oversupply during the lockdown (Lockdown, 5+ $>$ Feasible, 5+). The pandemic accelerated telework adoption by approximately 15 percentage points. Notably, the share of employees teleworking two to three days increased disproportionately, while full-time remote work even decreased. Panel a of Figure 4.7 presents these results visually.

While a majority (83.72%) of those with teleworkable jobs work from home, employer constraints are still prevalent (table (11), row *Budget*). To assess the extent of these constraints, refer to table (51), which cross-tabulates *Budget* and *Free-choice*. The upper triangular matrix indicates the share of employees who desire more frequent telework but are constrained. For instance, the first row, second column shows 6.23% who wish to telework one day but are not allowed to. Totaling 26.47% across the upper triangular matrix, highlights significant binding constraints. Understanding employer perspectives is crucial for interpreting telework frequencies.

Figure 4.6 illustrates current telework distribution across weekdays for full-time and part-time employees. Mondays and Fridays are preferred telework days: Full-time employed favor Fridays, while part-time employed favor Mondays (potentially not working at all on Fridays). A preference for Mondays and Fridays can be observed among full-time employed teleworking at least three days a week.

Simulations based on telework access and frequency distributions project potential telework shares under alternative scenarios (panel b, Figure 4.7). Implied home office shares under free-choice frequencies substantially increase, notably peaking on Fridays with nearly half of the workforce teleworking from home. Tuesdays and Thursdays show lower shares, suggesting varied impacts on transport infrastructure load across weekdays. These insights underline the need for separate analysis of Fridays and Tuesdays to Thursdays when examining telework's impact on transport demand.

Given these pandemic-driven shifts and the remaining potential, reconsidering the effect on mobility tool ownership is pertinent. As discussed in Section 4.1, this higher-order effect has been overlooked in previous studies. While group differences in ownership (panel a and b, Figure 4.8) suggest teleworkers more commonly own a half-fare card and slightly more often bicycles or E-bikes, car ownership and PT subscriptions are marginally lower among teleworkers. Panel b highlights distinct mobility tool compositions among those teleworking five or more days weekly, notably lower car and PT subscription ownership, the predominant commuting modes in Switzerland. However, simple group comparison might not portray the full picture as teleworkers likely constitute a special group with different

FREQUENCY

(11)

	0	1	2	3	4	5+	Sum
Budget*	16.28	9.15	21.25	8.94	2.68	41.7	100
Current	60.01	12.23	11.81	7.44	4.9	3.59	100
Feasible	33.83	16.03	13.57	11.57	9.67	15.34	100
Free-choice*	8.67	25.18	24.93	20.48	11.3	9.44	100
Lockdown	43.02	6.17	7.44	5.57	7.49	30.31	100
Pre-COVID	74.16	9.55	4.98	1.62	2.99	6.7	100

BINARY

(12)

	No	Yes	Sum
Can	38.41	61.59	100
May*	16.28	83.72	100
Want*	8.67	91.33	100
Do	60.01	39.99	100

CONTINGENCY

(21)*
Current / Budget

Current \ Budget	0	1	2	3	4	5+	Sum
0	16.28	3.83	2.75	1.09	0.07	11.28	35.3
1	0	4.77	4.51	0.62	0.36	9.57	19.83
2	0	0.28	9.94	1.82	0.44	6.64	19.12
3	0	0	2.77	3.65	0.6	5.06	12.08
4	0	0.16	1.14	1.42	0.91	4.21	7.84
5+	0	0.1	0.14	0.35	0.31	4.94	5.84
Sum	16.28	9.15	21.25	8.94	2.68	41.7	100

(22)*
Can / May

Can \ May	No	Yes	Sum
No	0	0	0
Yes	16.28	83.72	100
Sum	16.28	83.72	100

(31)*
Current / Free-choice

Current \ Free-choice	0	1	2	3	4	5+	Sum
0	8.03	15.25	8.55	2.32	0.5	0.65	35.3
1	0.37	8.52	7.11	3	0.35	0.48	19.83
2	0.24	1.26	7.29	7.54	2.37	0.41	19.12
3	0	0	1.1	5.35	3.46	2.17	12.08
4	0	0	0.89	1.57	3.99	1.38	7.84
5+	0.02	0.14	0	0.69	0.62	4.36	5.84
Sum	8.67	25.18	24.93	20.48	11.3	9.44	100

(32)*
Can / Want

Can \ Want	No	Yes	Sum
No	0	0	0
Yes	8.67	91.33	100
Sum	8.67	91.33	100

(41)
Current / Feasible

Current \ Feasible	0	1	2	3	4	5+	Sum
0	33.83	12.23	5.35	3.68	2.29	2.64	60.01
1	0	3.44	3.57	2.45	1.11	1.66	12.23
2	0	0.35	3.35	2.7	2.81	2.6	11.81
3	0	0	0.83	1.96	1.58	3.07	7.44
4	0	0	0.38	0.74	1.76	2.02	4.9
5+	0	0	0.08	0.04	0.12	3.36	3.59
Sum	33.83	16.03	13.57	11.57	9.67	15.34	100

(42)*
Can / Do

Can \ Do	No	Yes	Sum
No	38.27	0.14	38.41
Yes	21.74	39.85	61.59
Sum	60.01	39.99	100

(51)*
Budget / Free-choice

Budget \ Free-choice	0	1	2	3	4	5+	Sum
0	2.8	6.23	4.78	1.57	0.36	0.54	16.28
1	1.02	3.05	2.8	1.71	0.32	0.24	9.15
2	1.19	3.19	5.37	7.2	2.78	1.52	21.25
3	0.61	0.69	0.99	3.82	1.88	0.96	8.94
4	0.07	0.49	0.31	0.3	0.93	0.59	2.68
5+	2.98	11.53	10.68	5.88	5.04	5.59	41.7
Sum	8.67	25.18	24.93	20.48	11.3	9.44	100

(52)*
May / Want

May \ Want	No	Yes	Sum
No	2.8	13.48	16.28
Yes	5.87	77.85	83.72
Sum	8.67	91.33	100

(61)*
Budget / Feasible

Budget \ Feasible	0	1	2	3	4	5+	Sum
0	0	8.96	2.38	1.91	1.42	1.6	16.28
1	0	2.44	2.1	2.1	0.65	1.85	9.15
2	0	0.83	7.16	4.41	4.38	4.47	21.25
3	0	0.09	1.05	3.28	1.94	2.57	8.94
4	0	0	0.04	0.53	0.65	1.45	2.68
5+	0	10.6	7.43	6.25	5.66	11.77	41.7
Sum	0	22.92	20.17	18.49	14.71	23.72	100

(62)*
May / Do

May \ Do	No	Yes	Sum
No	16.28	0	16.28
Yes	19.02	64.7	83.72
Sum	35.3	64.7	100

(71)*
Free-choice / Feasible

Free-choice \ Feasible	0	1	2	3	4	5+	Sum
0	0	3.69	2.03	0.71	1.1	1.13	8.67
1	0	13.35	5.84	3.22	1.54	1.24	25.18
2	0	5.02	8.09	5.19	3.09	3.54	24.93
3	0	0.64	3.02	7.32	3.14	6.37	20.48
4	0	0.04	0.89	1.08	4.96	4.33	11.3
5+	0	0.19	0.29	0.97	0.87	7.12	9.44
Sum	0	22.92	20.17	18.49	14.71	23.72	100

(72)*
Want / Do

Want \ Do	No	Yes	Sum
No	8.03	0.63	8.67
Yes	27.27	64.06	91.33
Sum	35.3	64.7	100

*Population where telework is feasible (Can == Yes), *Budget:* Max. number of days allowed to telework, *Current:* Telework frequency as of survey date (June – August 2023), *Feasible:* Max. number of teleworking days feasible given job situation, *Free-choice:* Free-choice telework frequency (given job situation), *Lockdown:* Telework frequency during COVID-related lockdowns, *Pre-COVID:* Telework frequency before the COVID-pandemic, *Can:* Job is teleworkable, *May:* Employer allows teleworking, *Want:* Respondent wants to telework, *Do:* Respondent teleworks.

Table 4.5: Telework distributions and contingency tables.

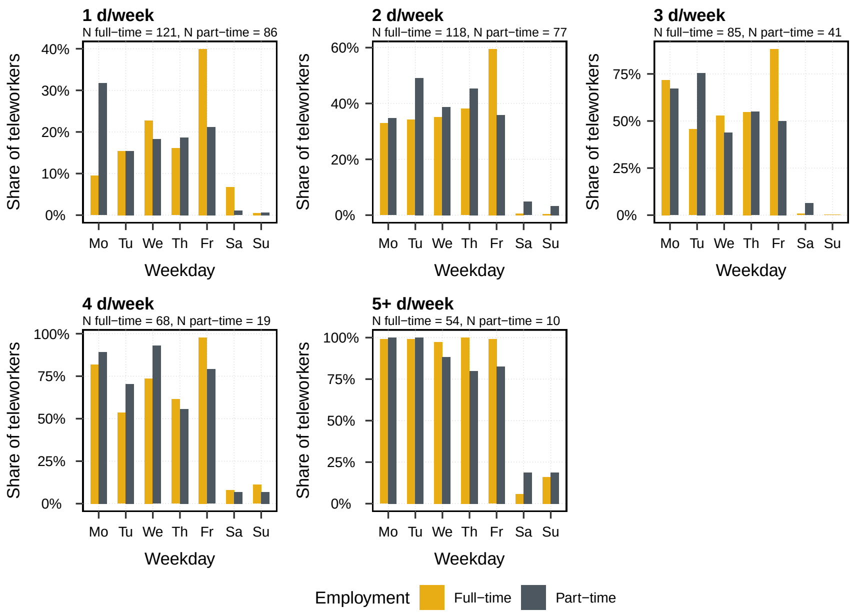

FIGURE 4.6: Distribution of telework shares across weekdays by number of teleworking days, for teleworking population only. Differentiating between full-time and part-time employed.

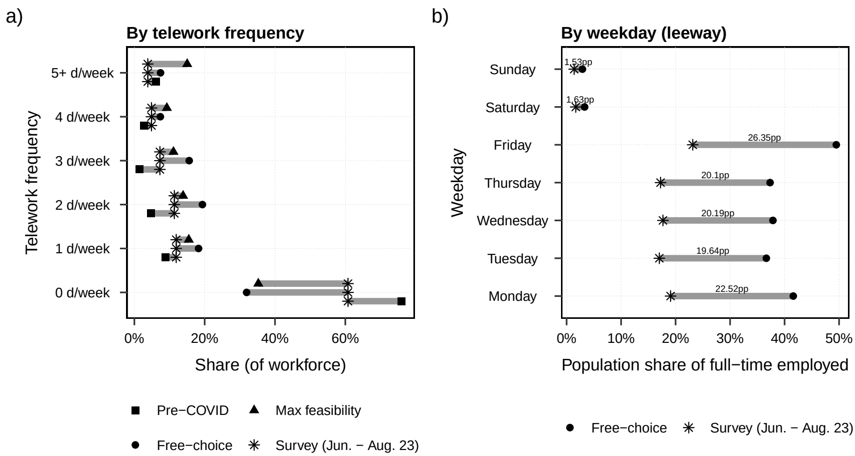

FIGURE 4.7: Evolution of telework frequency shares, before, during and after the pandemic (panel a), and potential leeway for teleworking shares on weekdays (panel b). Workforce population only.

mobility tool preferences even in the absence of the telework treatment (selection bias).

Therefore, clearer trends emerge from stated preference data where telework treatment was exogenous (see discussion in Section 4.2.4). Fully remote employees exhibit unique characteristics, evidenced by trends in (E-)bike and car ownership reversals, alongside linear trends in half-fare card and bike ownership increases, and declines in car ownership and PT subscriptions, particularly evident beyond four telework days weekly.

4.5 EFFECT OF TELEWORK ON MOBILITY TOOL OWNERSHIP

To assess the telework treatment effects, we conducted simple probit regressions, regressing telework frequency on mobility tool ownership. Due to observed non-linearities, separate coefficients were estimated for each telework frequency. Further distinctions were made between E-bikes and regular bikes, as well as between national and regional PT season tickets (ST). Results including estimates and standard errors are presented in Table 4.6. Bootstrapped ownership shares derived from these probit models are illustrated in Figure 4.9.

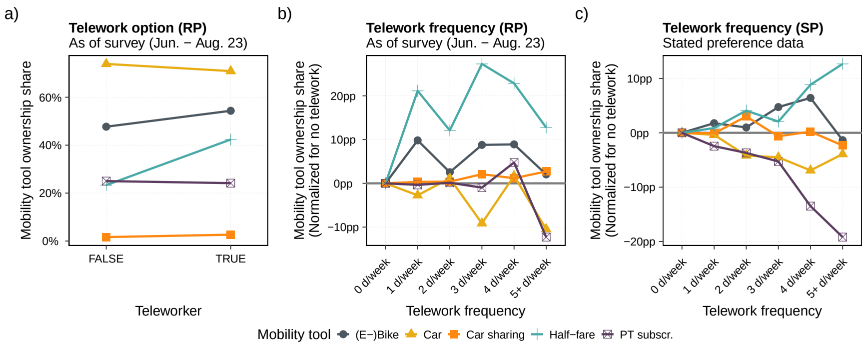

FIGURE 4.8: Comparison of mobility tool ownership shares by telework status and frequency. Panel a and b reflect ownership as of the survey period (June-August 2023), panel c is based on stated preference choices.

	Bike	Car	Car sharing	E-bike	National ST	Half-fare	Regional ST
(Intercept)	−0.06	−0.22***	−1.22***	−0.14**	−0.30***	0.03	0.01
	(0.07)	(0.04)	(0.06)	(0.05)	(0.06)	(0.04)	(0.06)
1 d/week	−0.02	−0.01	−0.00	0.07	−0.09	0.02	−0.05
	(0.11)	(0.06)	(0.08)	(0.07)	(0.09)	(0.06)	(0.09)
2 d/week	0.02	−0.11	0.15	0.03	−0.09	0.10	−0.10
	(0.11)	(0.06)	(0.08)	(0.08)	(0.09)	(0.06)	(0.09)
3 d/week	0.14	−0.12	−0.03	0.10	−0.16	0.05	−0.13
	(0.11)	(0.07)	(0.09)	(0.08)	(0.10)	(0.07)	(0.10)
4 d/week	0.20	−0.18*	0.01	0.15	−0.39**	0.22**	−0.36**
	(0.14)	(0.08)	(0.10)	(0.10)	(0.12)	(0.08)	(0.11)
5 d/week	−0.06	−0.10	−0.13	−0.03	−0.51***	0.33**	−0.54***
	(0.17)	(0.10)	(0.14)	(0.12)	(0.15)	(0.10)	(0.15)
AIC	1664.14	4841.47	2603.35	3358.74	2349.83	4986.28	2439.51
BIC	1694.65	4878.64	2640.51	3393.50	2382.95	5023.44	2472.39
Log Likelihood	−826.07	−2414.73	−1295.67	−1673.37	−1168.91	−2487.14	−1213.75
Deviance	1652.14	4829.47	2591.35	3346.74	2337.83	4974.28	2427.51
Num. obs.	1195	3620	3620	2425	1846	3620	1774

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1;
ST = Season ticket

TABLE 4.6: Simple probit models regressing telework frequency (as an indicator) on mobility tool ownership.

Consistent with earlier observations, the overall trends remain unchanged (as expected). Notably, significant telework treatment effects were observed only for frequencies of four days per week or more, particularly impacting PT subscriptions (half-fare card, national, and regional season tickets). These effects are evident as individuals at higher telework frequencies opt to cancel their season tickets in favor of the half-fare card. Conversely, no significant substitution effect was observed for car ownership, though it may play a role for (E-)bikes at lower telework frequencies. Contrary, there is some indication that car as the other main commuting mode looses some ownership share while not as pronounced as for PT subscriptions and with the before mentioned reversal for fully remote workers.

4.6 CONCLUSION

There has been enduring interest in the complex interplay between telework and mobility behavior, particularly regarding their implications for energy consumption and broader climate considerations. The COVID-19 pandemic acted as a catalyst for the widespread adoption of telework, reigniting academic discussions on its impact. In Switzerland, our data indicates a 15 percentage point increase in the teleworking population during the pandemic, with a notable rise in those opting for two to three teleworking days. The comprehensive dataset gathered for this study uniquely positions us to analyze the telework-related shifts brought about by the pandemic in Switzerland, including distinctions among those capable, permitted, and desiring to telework, as well as the potential for further expansion of telework practices.

The primary objective of this paper was to detail the survey methodology and present the collected data. Initially, 10'441 addresses were obtained from the Federal Statistical Office, with 3'234 respondents completing the introductory survey. Eligible telework participants were subsequently invited to participate in two stated preference experiments: One exploring preferences for hybrid work arrangements and another examining the relationship between telework and mobility tool ownership (MTO). A total of 922 respondents completed all three stages of the survey. The dataset supports a wide array of telework-related research questions, available for future academic exploration.

Our findings underscore Switzerland's unique telework potential, with over 60% of the workforce having jobs amenable to telework. Of these, 91.33% express a desire to telework, underscoring widespread interest

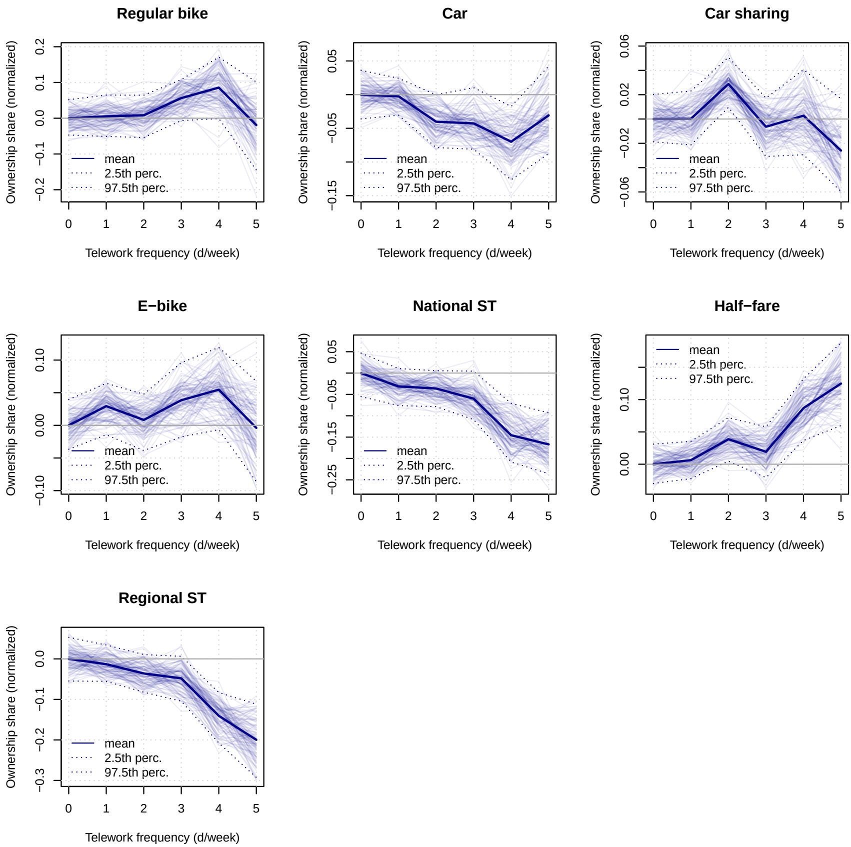

FIGURE 4.9: Bootstrapped ownership shares based on probit models linking telework frequency to ownership choices (based on the models presented in Table 4.6). Each line corresponds to the predictions based on one bootstrap sample. ST denotes season ticket.

in hybrid work arrangements. Despite this potential, there remains a 20 percentage point gap between telework-capable individuals and those currently teleworking. Although a majority (83.72%) of telework-capable individuals can work from home, employer-imposed constraint restrict telework for approximately one-fourth (26.47%) of these individuals who wish to telework more frequently.

Mondays and Fridays are generally preferred as teleworking days. Through simulation exercises that account for telework access, frequency distributions, and weekday preferences, we demonstrated strong variability, potentially translating to similar variability in transport network loads across weekdays. Notably, Fridays warrant separate analysis when assessing telework's impact on transport demand.

Various higher-order effects have been proposed that may influence the overall climate impact of telework, supplementing the reduction in commute-related emissions. This study contributes by examining a previously overlooked higher-order effect: The relationship between telework and mobility tool ownership. We argue against simplistic group comparisons, highlighting the endogeneity of telework supply which introduces potential bias into analyses if not accounted for. Our analysis of stated preference data reveals no direct adverse impact of telework on climate through a shift from public transport (PT) subscriptions to car ownership. Instead, teleworkers tend to substitute PT subscriptions with half-fare cards, particularly at higher frequencies of telework (4+ days per week). However, this shift may influence household-level mode choice, potentially favoring car use where households retain cars but forego PT subscriptions. Presently, only about 8% of the workforce teleworks four or five days a week, suggesting that PT subscriptions are still attractive contrary initial concerns of PT service providers. Furthermore, our findings indicate that these second-round adverse effects, while theoretically significant, are practically negligible.

5

ON THE VALUATION OF TELEWORK BASELINE PREFERENCES

The proof of the pudding is in the eating.

While the home office frequency choice is well researched, applicable work arrangement attributes are usually not known and therefore omitted. The goal of our work is to elicit the attractiveness of different hybrid work policies as well as their implications for home office frequencies. We hypothesize that in the absence of any incentive schemes or constraints, employees would choose their stated free choice frequency (baseline preference) and any deviation from it has to be attributed to the work arrangement. Multinomial logit (work arrangement choice) and ordinal logistic regression (frequency choice) models are employed, leveraging stated preference data uniquely collected for this purpose. We find that salary adjustments provide the biggest lever both in terms of attractiveness of the arrangement and its elasticity effect on telework supplied. However, deviation from the baseline is very hard to achieve with our proposed incentives. This indicates that baseline preferences are substantial and the marginal home office day is valued highly.

This chapter is loosely based on the following paper	Heimgartner D. and K. W. Axhausen (2024) Hybrid Work Arrangement Choices and Its Implications for Home Office Frequencies, paper presented at the *103rd Annual Meeting of the Transport Research Board (TRB 2024), Washington, D.C.*
Author contributions	Study conception and design: all authors; analysis and interpretation of results: D. Heimgartner; original draft: D. Heimgartner; writing, reviewing and editing: all authors. All authors reviewed and approved the final manuscript.

The following changes were made

Most of the original text became part of the paper under review, underlying Chapter 4 and is not repeated here. The original analysis modeled the telework frequency and used the baseline preference as explanatory variable. Here, we model the deviation from the baseline directly. Further, the random error component was added. While the qualitative conclusions did not change, modeling results did, with elasticities being even smaller. The methods section and the discussion of the results were adjusted accordingly.

5.1 INTRODUCTION

Chapter 4 portrayed the telework landscape in Switzerland, where we have noted, that employees would like to telework more often than current. We now ask, whether work arrangement characteristics could be part of the explanation, (dis-) incentivizing employees back to the office.

The goal is to elicit the attractiveness of different hybrid work policies as well as their implications for telework frequencies. We hypothesize that in the absence of any incentive schemes, employees would choose their stated free choice frequency (referred to as the baseline preference) and any deviation from it has to be attributed to the work arrangement. We then reflect on whether or not the implied sensitivities are large enough to explain the discrepancy between the status quo (1.65 days/week) and the free choice (2.31 days/week).

The question is investigated based on the stated preference (SP) data, collected as outlined in Section 4.2.3. We employ multinomial logistic regression (MNL) to elicit the attractiveness of the proposed policies and ordered logistic regression (OL) with random error components to estimate the impact of the chosen attributes on the telework frequency. Marginal probability effects and elasticities are then computed to scrutinize whether or not the effect strength is large enough to explain the aforementioned discrepancy.

5.2 METHODS

In this section we present the modeling methodology for the discrete work arrangement choice and the impact of the work arrangement on the telework frequency (modeled as the deviation from the baseline preference). The first model is a multinomial logit discrete choice model (MNL) whereas the subsequent choice is modeled through an ordinal logistic regression (OL) with random error components.

We now describe the two modeling frameworks separately, starting with the MNL: Let's recall that each decision maker n was asked to choose between two unlabelled work arrangements j in choice scenario t. The decision maker maximizes utility of the form $U_{njt} = V_{njt} + \varepsilon_{njt}$, where V_{njt} is the observed part of utility and ε_{njt} represents unobserved factors which follow a Gumbel (type I extreme value) distribution. The modeler assumes that V_{njt} can be expressed as $\beta' x_{njt}$, where x_{njt} is a vector of observed variables relating to alternative j. It can be shown that the probability of observing decision maker n choosing alternative j (i.e., $V_{njt} > V_{nj't}, \forall j \neq j'$) in choice occasion t is (Train, 2009, Chapter 3)

$$P_{njt} = \frac{\exp(\beta' x_{njt})}{\sum_j \exp(\beta' x_{njt})}. \tag{5.1}$$

The resulting likelihood can be written as

$$L(\beta) = \prod_n^N \prod_j^J \prod_t^{T_n} (P_{njt})^{y_{njt}} \tag{5.2}$$

where N is the total sample of decision makers, T_n the individual-specific total number of choice tasks and J the number of alternatives (in our case two). $y_{njt} = 1$ if person n chooses j and zero otherwise. However, computationally it is beneficial to remove the product operators by taking logs

$$\ell(\beta) = \sum_n^N \sum_j^J \sum_t^{T_n} y_{njt} \log(P_{njt}). \tag{5.3}$$

The model is estimated in R (R Core Team, 2024), using the **mixl** package (Molloy *et al.*, 2021a).

Let us introduce the ordinal logistic regression (proportional odds) model (see e.g., Train, 2009, Chapter 7): The latent variable is incompletely measured and takes the functional form $y^*_{nt} = \beta' x_{nt} + \mu_n + \varepsilon_{nt}$, where ε_{nt} is an error term assumed to follow a standard logistic distribution. y^*_{nt} is the latent propensity to deviate from the baseline (free choice telework frequency). $\mu_n \sim \mathcal{N}(0, \sigma)$ is an individual-specific random error component accounting for unobserved heterogeneity across individuals in their baseline telework frequency preferences (for random error components and mixed models, see, e.g., Train, 2009, Chapter 6). As y^*_{nt} increases and passes some unknown but estimable thresholds $(\tau_0, \ldots, \tau_{10})$, we move up from one ordinal outcome to the next higher. I.e., we observe the choice $y_{nt} = k$ according to

$$y_{nt} = \begin{cases} -5 & \text{if } -\infty < y^*_{nt} \leq \tau_0 \\ -4 & \text{if } \tau_0 < y^*_{nt} \leq \tau_1 \\ \vdots & \\ 5 & \text{if } \tau_{10} < y^*_{nt} \leq +\infty \end{cases} \tag{5.4}$$

This yields the following probability

$$\begin{aligned} P_{nkt} &= P(y_{nt} = k \mid x_{nt}, \mu_n) = P(\tau_{k-1} < y^*_{nt} \leq \tau_k) \\ &= P(\tau_{k-1} < \beta' x_{nt} + \mu_n + \varepsilon_{nt} \leq \tau_k) \\ &= \frac{1}{1 + \exp(\tau_k - \beta' x_{nt} - \mu_n)} - \frac{1}{1 + \exp(\tau_{k-1} - \beta' x_{nt} - \mu_n)}. \end{aligned} \tag{5.5}$$

The likelihood (“integrating out” the error component) can be written as

$$L(\beta, \tau) = \int \prod_n^N \prod_k^K \prod_t^{T_n} (P_{nkt})^{y_{nkt}} f(\mu_n)\, d\mu_n \tag{5.6}$$

where $y_{nkt} = 1$ if $y_{nt} = k$ was observed and zero otherwise. $f(\mu_n)$ is the PDF of a normal distribution with mean 0 and variance σ^2.

The model is estimated using the **ordinal** R-package (Christensen, 2023).

5.3 RESULTS AND DISCUSSION

We now discuss the modeling results, discussing the work arrangement choice and telework frequency choice separately.

5.3.1 *Work arrangement choice*

The estimation results of the MNL model are presented in Table 5.1. In addition to the conventional metrics and goodness of fit indicators, marginal probability effects (MPE) were computed. The MPE is the change in choice probability, attributed to a single variable and in comparison to its reference level. The reference levels are noted in brackets. For example, if two work arrangements are exactly the same, except that the first features a salary increase of 10% (per hour teleworked), while the second a deduction of 10%, then the probability that the first is chosen is 33.4 percentage points higher.

Overall, the results are intuitive with the expected signs. All attributes were found to be significant except for *Core hours* and *Desk sharing*. Having to work during regular working hours on home office days does not impact the choice. This is surprising because one of the benefits of telework is greater flexibility. The attribute, as presented, would imply that employees have to reside at their designated workstation during business hours.

Commenting on the effect size (marginal probability effects) the *Salary adjustments* play the most substantial role followed by *Work from anywhere* and *Hardware contribution*. Work from anywhere is roughly equivalent to the 10% salary increase (compared to the current hourly wage rate). The remaining attributes all have similar (positive or negative) smaller magnitudes.

The utility weights traced out and their behavioral consequences seem to contradict standard economic theory: There are three monetary attributes (*Salary adjustments, Additional cost* and *Hardware contribution*) all implying a utility equivalent of a marginal monetary unit (Swiss franc in our case). However, the marginal Swiss franc (CHF) seems to be valued differently depending on the reason it was received. Average income is 7'514 CHF, average monthly additional costs 523 CHF and necessary annual home office infrastructure investments 2'186 CHF (these numbers were collected in the survey). For example, 100% participation of additional costs easily compensates hardware investments. Nevertheless, estimates and implied MPE widely differ. There might be an argument on the grounds of what employees deem fair (or unfair), necessary (or unnecessary) as monetary compensation for expenses linked to telework. Similarly, decreasing the salary yields a stronger negative effect than increasing it by the same percentage amount.

Last, coordinating office presence on Mondays and Fridays reduces the attractiveness of the work arrangement. This is in line with the current distribution of the home office days over the week, where we observe a higher teleworking share on these days.

	Estimate	Std. Error	MPE
ASC	0.038	0.054	
Co-ordination (None)			
Corner days	-0.202^{**}	0.075	-0.035
Middle days	-0.158	0.082	-0.027
Core hours (None)			
Regular working hours	0.028	0.056	0.005
Help/training (No)			
Yes	0.219^{***}	0.053	0.038
Salary adj. (-10%)			
No salary adj.	1.355^{***}	0.088	0.237
+10%	1.788^{***}	0.102	0.334
Add. cost (No part.)			
50% participation	0.197^{**}	0.072	0.034
100% participation	0.158^{*}	0.079	0.028
Hardware contrib. (None)			
50% participation	0.178^{*}	0.076	0.031
100% participation	0.335^{***}	0.078	0.058
Work from anywhere (No)			
Yes	0.440^{***}	0.059	0.077
Desk sharing (No)			
Yes	-0.055	0.060	-0.010
N obs.	2037.000		
N params.	13.000		
LL (start)	-1411.941		
LL (final)	-1070.084		
McFadden R^2	0.242		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
MPE = Marginal probability effect;

Table 5.1: MNL estimation results.

5.3.2 *Telework frequency choice*

The estimation results of the OL model are presented in Table 5.2. Elasticities (expressed in number of days deviating from the baseline) are shown in the last column: For example, the elasticity corresponding to a salary increase by 10% (compared to the reference of a 10% salary reduction) reads 0.04 d/week. Overall, the computed elasticities are very small, suggesting that the proposed attributes have little lever to (dis-) incentivize deviations from the baseline preference.

	Estimate	Std. Error	Elast.
σ	6.409^{***}	0.057	
Co-ordination (None)			
Corner days	-0.372^{*}	0.157	−0.021
Middle days	-0.678^{***}	0.174	−0.034
Core hours (None)			
Regular working hours	0.085	0.134	0.004
Help/training (No)			
Yes	0.130	0.134	0.007
Salary adj. (-10%)			
No salary adj.	0.496^{*}	0.219	0.020
+10%	0.899^{***}	0.218	0.041
Add. cost (No part.)			
50% participation	0.179	0.159	0.009
100% participation	0.320^{*}	0.161	0.016
Hardware contrib. (None)			
50% participation	0.201	0.168	0.009
100% participation	0.391^{*}	0.164	0.020
Work from anywhere (No)			
Yes	0.484^{***}	0.135	0.024
Desk sharing (No)			

Continued on next page

Table 5.2 – *Continued from previous page*

	Estimate	Std. Error	Elast.
Yes	-0.064	0.133	-0.003
-4 | -3	-15.603^{***}	1.002	
-3 | -2	-13.123^{***}	0.728	
-2 | -1	-9.829^{***}	0.552	
-1 | 0	-4.463^{***}	0.426	
0 | 1	4.069^{***}	0.477	
1 | 2	9.547^{***}	0.583	
2 | 3	13.160^{***}	0.684	
3 | 4	17.803^{***}	1.073	
4 | 5	19.764^{***}	1.360	
N obs.	2037.000		
N params.	22.000		
LL (start)	-4690.366		
LL (final)	-2006.408		
McFadden R^2 (zero)	0.572		
McFadden R^2 (intercept)	0.326		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Elast. = Elasticity (d/week) ;

Table 5.2: OL estimation results.

The estimated standard deviation (parameter) corresponding to the random error component (σ) is significant and quite substantial (see also the threshold estimates, ranging from -15.6 to 19.7 on the latent scale). This suggests that there are other (unobserved) factors nudging teleworkers to deviate from their baseline. Similarly, the baseline preference could be "imprecisely" measured or could have changed since the measurement.

5.4 CONCLUSION

We find that deviation from the baseline is very hard to achieve with our proposed (dis-) incentives. This indicates that baseline preferences are strong and that the marginal home office day is valued highly. Enticing teleworkers back to the office would need to offset these utility losses. It is easy to imagine, that foregone commuting during rush hours and the associated time being freed is larger than, for example, the 10% salary deduction (e.g., a full work day of 8 hours at 30 CHF/h yields 240 CHF/d and the deduction would imply minus 24 CHF). In light of the analysis, it is not surprising, that employers set a maximum number of allowed teleworking days and simply demand employees back to office. Employers do so because of feared productivity losses (e.g., through limited exchange and flow of ideas). However, it is questionable whether, first, such fears are justified and, second, whether potential productivity increases offset the employees' utility losses. Meanwhile, telework could be associated with potential welfare gains at the broader societal level with diminished vehicle miles driven and associated foregone negative externalities. While the negotiation on labor markets balance employers' and employees' preferences, the welfare gains are likely not part of the equations, leading to overall suboptimal levels of telework.

6

TOOLS

When solving a problem of interest, do not solve a more general problem as an intermediate step.
— Vladimir Vapnik

Selection bias may arise if unobserved factors simultaneously influence the selection process for who gets treated (or not), and the outcome of (not) receiving the treatment. Different methods exist to correct for this bias depending on whether longitudinal or cross-sectional data is available. A possible cure in the latter case (where the counterfactual treatment outcome is never observed) is to explicitly account for the arising error correlation and estimate the covariance matrix of the selection and outcome processes. This is known as endogenous switching regression. The R package **OPSR** introduced in this article provides an easy-to-use, fast and memory efficient interface to ordered probit switching regression, accounting for self-selection into an ordinal treatment. It handles log-transformed outcomes which need special consideration when computing conditional expectations and thus treatment effects. The reference manual can be found in Appendix A.3.1.

This chapter is based on the following paper

Heimgartner D. and X. Wang (2025) **OPSR**: A Package for Estimating Ordered Probit Switching Regression Models in R, *Jouranl of Statistical Software*, submitted.

Author contributions

Xinyi Wang and Daniel Heimgartner conceived the presented idea to formalize the findings of Wang and Mokhtarian (2024) into an R package. The theory presented in Section 6.2 stems from that work. Daniel Heimgartner implemented the functionality and R package architecture based on Xinyi Wang's original scripts, as well as drafted the paper. All authors discussed the results and contributed to the final manuscript.

The following changes were made

The model `fit_intercept` was excluded from the `texreg::screenreg()` call on Page 93.

6.1 INTRODUCTION

The goal of the program evaluation literature is to estimate the effect of a treatment program (e.g., a new policy, technology, medical treatment, or agricultural practice) on an outcome. To evaluate such a program, the "treated" are compared to the "untreated". In an experimental setting, the treatment can be (randomly) assigned by the researcher. However, in an observational setting, the treatment is not always exogenously prescribed but rather self-selected. This gives rise to a selection bias when factors (either observed or unobserved) influencing the treatment adoption also influence the outcome (also known as selection on observables and unobservables). Simple group comparison no longer yield an unbiased estimate of the treatment effect. In more technical terms, the counterfactual outcome of the treated ("if they had not been treated") does not necessarily correspond to the factual outcome of the untreated. For example, cyclists riding without a helmet (the "untreated") might be young and have a risk-seeking tendency. We therefore potentially overestimate the benefit of wearing a helmet if we compare the accident rate and/or crash severity rate between those who wear and do not wear helmets directly. Even if we may control age for the comparison, variables such as risk-seeking are not readily measured, and it may still be part of the error in applied research and thus leading cause of a selection bias.

To properly account for the selection bias, various techniques exist, both for longitudinal and cross-sectional data. In the first case, difference in differences is a widely adopted measure. In the latter case, instrumental variables, matching propensity scores, regression-discontinuity design, and the endogenous switching regression model have been applied (Wang and Mokhtarian, 2024). The endogenous switching regression model, an extension of Heckman's classic sample selection model, is particularly well-suited to correct for both selection on observables and unobservables (unlike other methods which only address and correct for selection on observables).

The seminal work by Heckman (1979) proposed a two-part model to address the selection bias that often occurs when modelling a continuous outcome which is only observable for a subpopulation. A very nice exposition of this model is given in Cameron and Trivedi (2005, Chapter 16).

The classical Heckman model consists of a probit equation and continuous outcome equation. A natural extension is then switching regression, where the population is partitioned into different groups (regimes) and separate parameters are estimated for the continuous outcome process of each group. This model is originally known as the Roy model (Cameron and Trivedi, 2005) or Tobit-5 model (Amemiya, 1985). These classical models (the Tobit models for truncated, censored or interval data and their extensions) are implemented in various environments for statistical computing and in R's (R Core Team, 2024) **sampleSelection** package (Toomet and Henningsen, 2008).

Many different variants can then be derived by either placing different distributional assumptions on the errors and/or how the latent process manifests into observed outcomes (i.e., the dependent variables can be of various types, such as binary, ordinal, censored, or continuous) more generally known as conditional mixed-process (CMP) models. CMP models comprise a broad family involving two or more equations featuring a joint error distribution assumed to be multivariate normal. The Stata (StataCorp, 2023) command `cmp` (Roodman, 2011) can fit such models. The variant at the heart of this paper is an ordered probit switching regression (OPSR) model, with ordered treatments and continuous outcome. Throughout the text we use the convention that OPSR refers to the general methodology, while **OPSR** refers specifically to the package.

OPSR is available as a Stata command, `oheckman` (Chiburis and Lokshin, 2007), which however, does not allow distinct specifications for the continuous outcome processes (i.e., the same explanatory variables must be used for all treatment groups). The relatively new R package **switchSelection** (Potanin, 2024) allows to estimate multivariate and multinomial sample selection and endogenous switching models with multiple outcomes. These models are systems of ordinal, continuous and multinomial equations and thus nest OPSR as a special case.

OPSR is tailored to one particular method, easy to use (understand, extend and maintain), fast and memory efficient. Unlike the implementations mentioned, this approach accommodates log-transformed continuous outcomes. Log transformation is a widely used technique in real-world applications to enhance data normality and meet model assumptions. In multi-layer models like OPSR, special consideration is required for computing conditional expectations on the original scale (i.e., back-transform from the log scale) to ensure meaningful real-world interpretations. **OPSR** obeys to R's implicit modeling conventions (by providing a formula interface to a fitter function and by extending the established generics such as `summary()`, `predict()`, `update()`, `anova()` among others) and produces production-grade output tables. This work generalizes the learnings from Wang and Mokhtarian (2024) and makes the OPSR methodology readily available. The mathematical notation presented here translates to code almost verbatim which hopefully serves a pedagogical purpose for the curious reader.

The remainder of this paper is organized as follows: Section 6.2 outlines the ordered probit switching regression model, lists all the key formulas underlying the software implementation and details **OPSR**'s architecture. In Section 6.3 the key functionality is demonstrated both on simulated data and the data from Wang and Mokhtarian (2024) which we use to reproduce their core model. Further, it is shown, that **OPSR** can be used to estimate the well-known Tobit-5 model and yields the same parameters as the implementation in **sampleSelection**. The case study in Section 6.4 leverages tracking data from the TimeUse+ study (Winkler *et al.*, 2024) investigating telework treatment effects on weekly distance traveled. There, we also compare the OPSR model to a model not accounting for error correlation and discuss the implications for treatment effects. The summary in Section 6.5 concludes.

6.2 MODEL AND SOFTWARE

In the following, we outline the ordered probit switching regression model as well as list all the key formulas underlying the software implementation. **OPSR** follows the R-typical formula interface to a workhorse fitter function. Its architecture is detailed after the mathematical part.

As alluded, OPSR contains two layers: One process governs the ordinal outcome and separate processes (for each ordinal outcome) govern the continuous outcomes. The ordinal outcome can also be thought of as a regime or treatment. In the subsequent exposition, we will refer to the two processes as *selection* and *outcome* process.

We borrow the notation from Wang and Mokhtarian (2024) where also all the derivations are detailed. For a similar exhibition, Chiburis and Lokshin (2007) can be consulted. Individual subscripts are suppressed throughout, for simplicity.

Let $\mathcal{Z}$ be a latent propensity governing the selection outcome

$$\mathcal{Z} = \boldsymbol{W}\boldsymbol{\gamma} + \epsilon, \tag{6.1}$$

where $\boldsymbol{W}$ represents the vector of attributes of an individual, $\boldsymbol{\gamma}$ is the corresponding vector of parameters and $\epsilon \sim \mathcal{N}(0,1)$ a normally distributed error term.

As $\mathcal{Z}$ increases and passes some unknown but estimable thresholds, we move up from one ordinal treatment to the next higher level

$$Z = j \quad \text{if } \kappa_{j-1} < \mathcal{Z} \leq \kappa_j, \tag{6.2}$$

where Z is the observed ordinal selection variable, $j = 1, \ldots, J$ indexes the ordinal levels of Z, and κ_j are the thresholds (with $\kappa_0 = -\infty$ and $\kappa_J = \infty$). Hence, there are $J-1$ thresholds to be estimated. The probability that an individual self-selects into treatment group j is

$$\begin{aligned} \mathsf{P}[Z = j] &= \mathsf{P}[\kappa_{j-1} < \mathcal{Z} \leq \kappa_j] \\ &= \mathsf{P}[\kappa_{j-1} - \boldsymbol{W\gamma} < \epsilon \leq \kappa_j - \boldsymbol{W\gamma}] \\ &= \Phi(\kappa_j - \boldsymbol{W\gamma}) - \Phi(\kappa_{j-1} - \boldsymbol{W\gamma}). \end{aligned} \tag{6.3}$$

where $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution.

The outcome model for the j^{th} treatment group is expressed as

$$y_j = \boldsymbol{X_j\beta_j} + \eta_j, \tag{6.4}$$

where y_j is the observed continuous outcome, $\boldsymbol{X_j}$ the vector of observed explanatory variables associated with the j^{th} outcome model, $\boldsymbol{\beta_j}$ is the vector of associated parameters, and $\eta_j \sim \mathcal{N}(0, \sigma_j^2)$ is a normally distributed error term. At this point it should be noted that $\boldsymbol{X_j}$ and $\boldsymbol{W}$ may share some explanatory variables but not all, due to identification problems otherwise (Chiburis and Lokshin, 2007).

The key assumption of OPSR is now that the errors of the selection and outcome models are jointly multivariate normally distributed

$$\begin{pmatrix} \epsilon \\ \eta_1 \\ \vdots \\ \eta_j \\ \vdots \\ \eta_J \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ \vdots \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_1\sigma_1 & \cdots & \rho_j\sigma_j & \cdots & \rho_J\sigma_J \\ \rho_1\sigma_1 & \sigma_2^2 & & & & \\ \vdots & & \ddots & & & \\ \rho_j\sigma_j & & & \sigma_j^2 & & \\ \vdots & & & & \ddots & \\ \rho_J\sigma_J & & & & & \sigma_J^2 \end{pmatrix} \right), \tag{6.5}$$

where ρ_j represents the correlation between the errors of the selection model (ϵ) and the j^{th} outcome model (η_j). If the covariance matrix should be diagonal (i.e., no error correlation), no selection-bias exists and the selection and outcome models can be estimated separately.

As shown in Wang and Mokhtarian (2024), the log-likelihood of observing all individuals self-selecting into treatment j and choosing continuous outcome y_j can be expressed as

$$\begin{aligned}\ell(\theta \mid \boldsymbol{W}, \boldsymbol{X}_j) = \sum_{j=1}^{J} \sum_{\{j\}} \Bigg\{ \ln\left[\frac{1}{\sigma_j}\phi\left(\frac{y_j - \boldsymbol{X}_j\boldsymbol{\beta}_j}{\sigma_j}\right)\right] \quad + \\ \ln\Bigg[\Phi\left(\frac{\sigma_j(\kappa_j - \boldsymbol{W}\gamma) - \rho_j(y_j - \boldsymbol{X}_j\boldsymbol{\beta}_j)}{\sigma_j\sqrt{1-\rho_j^2}}\right) - \\ \Phi\left(\frac{\sigma_j(\kappa_{j-1} - \boldsymbol{W}\gamma) - \rho_j(y_j - \boldsymbol{X}_j\boldsymbol{\beta}_j)}{\sigma_j\sqrt{1-\rho_j^2}}\right)\Bigg]\Bigg\}\end{aligned} \tag{6.6}$$

where $\sum_{\{j\}}$ means the summation of all the cases belonging to the j^{th} selection outcome, $\phi(\cdot)$ and $\Phi(\cdot)$ are the density and cumulative distribution function of the standard normal distribution.

The conditional expectation can be expressed as

$$\begin{aligned}\mathsf{E}[y_j \mid Z = j] &= \boldsymbol{X}_j\boldsymbol{\beta}_j + \mathsf{E}[\eta_j \mid \kappa_{j-1} - \boldsymbol{W}\gamma < \epsilon \leq \kappa_j - \boldsymbol{W}\gamma] \\ &= \boldsymbol{X}_j\boldsymbol{\beta}_j - \rho_j\sigma_j\frac{\phi(\kappa_j - \boldsymbol{W}\gamma) - \phi(\kappa_{j-1} - \boldsymbol{W}\gamma)}{\Phi(\kappa_j - \boldsymbol{W}\gamma) - \Phi(\kappa_{j-1} - \boldsymbol{W}\gamma)},\end{aligned} \tag{6.7}$$

where the (negative) fraction is the ordered probit switching regression model counterpart to the inverse Mills ratio (IMR) term of a binary switching regression model (because of its resemblance, we will also refer to this fraction as inverse Mills ratio in the OPSR case). We immediately see, that regressing $\boldsymbol{X}_j$ on y_j leads to an omitted variable bias if $\rho_j \neq 0$ which is the root cause of the selection bias. However, the IMR can be pre-computed based on an ordered probit model and then included in the second stage regression, which describes the Heckman correction (Heckman, 1979). It should be warned, that since the Heckman two-step procedure includes an estimate in the second step regression, the resulting OLS standard errors and heteroskedasticity-robust standard errors are incorrect (Greene, 2002).

To obtain unbiased treatment effects, we must further evaluate the "counterfactual outcome", which reflects the expected outcome under a counterfactual treatment (i.e., for $j' \neq j$)

$$\begin{aligned}\mathsf{E}[y_{j'} \mid Z = j] &= \boldsymbol{X}_{j'}\boldsymbol{\beta}_{j'} + \mathsf{E}[\eta_{j'} \mid \kappa_{j-1} - \boldsymbol{W}\boldsymbol{\gamma} < \epsilon \leq \kappa_j - \boldsymbol{W}\boldsymbol{\gamma}] \\ &= \boldsymbol{X}_{j'}\boldsymbol{\beta}_{j'} - \rho_{j'}\sigma_{j'}\frac{\phi(\kappa_j - \boldsymbol{W}\boldsymbol{\gamma}) - \phi(\kappa_{j-1} - \boldsymbol{W}\boldsymbol{\gamma})}{\Phi(\kappa_j - \boldsymbol{W}\boldsymbol{\gamma}) - \Phi(\kappa_{j-1} - \boldsymbol{W}\boldsymbol{\gamma})}.\end{aligned} \tag{6.8}$$

Let's assume that $y_j = \ln(Y_j + \delta)$ in the previous equations. I.e., the continuous outcome was log-transformed as is usual in regression analysis. We have to note, that in such cases the Equations 6.7–6.8 provide the conditional expectation of the log-transformed outcome. Therefore we need to back-transform $Y_j = \exp(y_j) - \delta$ which yields

$$\begin{aligned}\mathsf{E}[Y_j \mid Z = j] = \exp&\left(\boldsymbol{X}_j\boldsymbol{\beta}_j + \frac{\sigma_j^2}{2}\right) \\ &\left[\frac{\Phi(\kappa_j - \boldsymbol{W}\boldsymbol{\gamma} - \rho_j\sigma_j) - \Phi(\kappa_{j-1} - \boldsymbol{W}\boldsymbol{\gamma} - \rho_j\sigma_j)}{\Phi(\kappa_j - \boldsymbol{W}\boldsymbol{\gamma}) - \Phi(\kappa_{j-1} - \boldsymbol{W}\boldsymbol{\gamma})}\right] - \delta\end{aligned} \tag{6.9}$$

for the factual case, and

$$\begin{aligned}\mathsf{E}[Y_{j'} \mid Z = j] = \exp&\left(\boldsymbol{X}_{j'}\boldsymbol{\beta}_{j'} + \frac{\sigma_{j'}^2}{2}\right) \\ &\left[\frac{\Phi(\kappa_j - \boldsymbol{W}\boldsymbol{\gamma} - \rho_{j'}\sigma_{j'}) - \Phi(\kappa_{j-1} - \boldsymbol{W}\boldsymbol{\gamma} - \rho_{j'}\sigma_{j'})}{\Phi(\kappa_j - \boldsymbol{W}\boldsymbol{\gamma}) - \Phi(\kappa_{j-1} - \boldsymbol{W}\boldsymbol{\gamma})}\right] - \delta\end{aligned} \tag{6.10}$$

for the counterfactual case (Wang and Mokhtarian, 2024).

This concludes the mathematical treatment and we briefly outline **OPSR**'s architecture which can be conceptualized as follows:

- We provide the usual formula interface to specify a model. To allow for multiple parts and multiple responses, we rely on the **Formula** package (Zeileis and Croissant, 2010).
- After parsing the formula object, checking the user inputs and computing the model matrices, the Heckman two-step estimator is called in `opsr_2step()` to generate reasonable starting values.

- These are then passed together with the data to the basic computation engine `opsr.fit()`. The main estimates are retrieved using maximum likelihood estimation by passing the log-likelihood function `loglik_cpp()` (Equation 6.6) to `maxLik()` from the **maxLik** package (Henningsen and Toomet, 2011).
- All the above calls are nested in the main interface `opsr()` which returns an object of class '`opsr`'. Several methods then exist to post-process this object as illustrated below.

The likelihood function `loglik_cpp()` is implemented in C++ using **Rcpp** (Eddelbuettel and Balamuta, 2018) and relying on the data types provided by **RcppArmadillo** (Eddelbuettel and Sanderson, 2014). Parallelization is available using OpenMP. This makes **OPSR** both fast and memory efficient (as data matrices are passed by reference).

6.3 ILLUSTRATIONS

We first illustrate how to specify a model using **Formula**'s extended syntax and simulated data. Then the main functionality of the package is demonstrated. We conclude this section by demonstrating some nuances, reproducing the core model of Wang and Mokhtarian (2024). Finally, we show that **OPSR** can also estimate the classic Tobit-5 model and matches the results obtained with the implementation from **sampleSelection**.

6.3.1 **OPSR** *core*

Let us simulate date from an OPSR process with three ordinal outcomes and distinct design matrices $\boldsymbol{W}$ and $\boldsymbol{X}$ (where $\boldsymbol{X} = \boldsymbol{X}_j \; \forall j$) by

```
R> sim_dat <- opsr_simulate()
R> dat <- sim_dat$data
R> head(dat)
```

```
  ys    yo      xs1    xs2    xo1     xo2
1  2 -1.26  0.44435 -0.538  1.263 -0.2869
2  2  3.80  0.01193  0.497 -0.326  1.8411
3  1  3.95 -0.00928 -1.442  1.330 -0.1568
4  2 -1.68 -0.30238 -1.113  1.272 -1.3898
5  1  1.50  0.49236 -1.015  0.415 -1.4731
6  2  2.20 -0.60272  0.567 -1.540 -0.0695
```

where `ys` is the selection dependent variable (or treatment group), `yo` the outcome dependent variable and `xs` respectively `xo` the corresponding explanatory variables.

Models are specified symbolically. A typical model has the form `ys | yo ~ terms_s | terms_o1 | terms_o2 | ...` where the `|` separates the two responses and process specifications. If the user wants to specify the same process for all continuous outcomes, two processes are enough (`ys | yo ~ terms_s | terms_o`). Hence the minimal `opsr()` interface call reads

```
R> fit <- opsr(ys | yo ~ xs1 + xs2 | xo1 + xo2, data = dat,
+    printLevel = 0)
```

where `printLevel = 0` omits working information during maximum likelihood iterations.

As usual, the fitter function does the bare minimum model estimation while inference is performed in a separate call to

```
R> summary(fit)

Call:
opsr(formula = ys | yo ~ xs1 + xs2 | xo1 + xo2, data = dat, printLevel = 0)

BFGS maximization, 102 iterations
Return code 0: successful convergence
Runtime: 0.224 secs
Number of regimes: 3
Number of observations: 1000 (152, 507, 341)
Estimated parameters: 19

Log-Likelihood: -2016
AIC: 4071
BIC: 4164
Pseudo R-squared (EL): 0.506
Pseudo R-squared (MS): 0.456
Multiple R-squared: 0.815 (0.836, 0.762, 0.847)

Estimates:
                Estimate Std. error t value Pr(> t)
kappa1           -1.9618     0.0932  -21.05 < 2e-16 ***
kappa2            0.8826     0.0615   14.36 < 2e-16 ***
s_xs1             0.9373     0.0570   16.44 < 2e-16 ***
s_xs2             1.4964     0.0712   21.01 < 2e-16 ***
o1_(Intercept)    0.9877     0.1440    6.86   7e-12 ***
o1_xo1            2.0512     0.0930   22.06 < 2e-16 ***
```

```
o1_xo2            1.0133     0.0712   14.23 < 2e-16 ***
o2_(Intercept)    0.9574     0.0463   20.67 < 2e-16 ***
o2_xo1           -0.9884     0.0435  -22.70 < 2e-16 ***
o2_xo2            1.5545     0.0412   37.73 < 2e-16 ***
o3_(Intercept)    1.0028     0.0909   11.03 < 2e-16 ***
o3_xo1            1.5766     0.0560   28.15 < 2e-16 ***
o3_xo2           -1.9227     0.0528  -36.44 < 2e-16 ***
sigma1            1.0442     0.0534   19.55 < 2e-16 ***
sigma2            1.0478     0.0316   33.12 < 2e-16 ***
sigma3            1.1717     0.0430   27.27 < 2e-16 ***
rho1              0.1696     0.1361    1.25 0.21279
rho2              0.3482     0.0639    5.45   5e-08 ***
rho3              0.3699     0.1077    3.44 0.00059 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Wald chi2 (null): 5071 on 8 DF, p-value: < 0
Wald chi2 (rho): 42.7 on 3 DF, p-value: < 0
```

The presentation of the model results is fairly standard and should not warrant further explanation with the following exceptions

1. The number of regimes along absolute counts are reported.
2. Pseudo R-squared (EL) is determined by comparing the log-likelihood of the specified model to that of the "equally likely" model, while Pseudo R-squared (MS) is obtained by comparing the log-likelihood of the specified model to that of the "market-share" model. These indicators reflect the goodness of fit for the selection process. The multiple R-squared is reported for all continuous outcomes collectively and for the regimes separately in brackets (i.e., only considering the continuous observations belonging to the respective treatment regime). These indicators reflect the goodness of fit for the outcome processes.
3. Coefficient names are based on the variable names as passed to the formula specification, except that `"s_"` is prepended to the selection coefficients, `"o[0-9]_"` to the outcome coefficients and the structural components `"kappa"`, `"sigma"`, `"rho"` (aligning with the letters used in Equation 6.6) are hard-coded (but can be over-written).
4. The coefficients table reports robust standard errors based on the sandwich covariance matrix as computed with help of the **sandwich**

package (Zeileis, 2006). `rob = FALSE` reports conventional standard errors.

5. Two Wald-tests are conducted. One, testing the null that all coefficients of explanatory variables are zero and two, testing the null that all error correlation coefficients (`rho`) are zero. The latter being rejected indicates that selection bias is an issue.

A useful benchmark is always the null model with structural parameters only. The null model can be derived from an ‘`opsr`’ model fit as follows

```
R> fit_null <- opsr_null_model(fit, printLevel = 0)
```

A model can be updated as usual

```
R> fit_intercept <- update(fit, . ~ . | 1)
```

where we have removed all the explanatory variables from the outcome processes.

Several models can be compared with a likelihood-ratio test using

```
R> anova(fit_null, fit_intercept, fit)

Likelihood Ratio Test

Model 1: ~Nullmodel
Model 2: ys | yo ~ xs1 + xs2 | 1
Model 3: ys | yo ~ xs1 + xs2 | xo1 + xo2
  logLik   Df  Test Restrictions Pr(>Chi)
1  -3293    8
2  -2835   13   917            5   <2e-16 ***
3  -2016   19  1636            6   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

If only a single object is passed, then the model is compared to the null model. If more than one object is specified a likelihood ratio test is conducted for each pair of neighboring models. As expected, both tests reject the null hypothesis.

Models can be compared side-by-side using the **texreg** package (Leifeld, 2013), which also allows the user to build production-grade tables as illustrated later.

```
R> texreg::screenreg(list(fit_null, fit),
+    include.pseudoR2 = TRUE, include.R2 = TRUE, single.row = TRUE)
```

```
=========================================================
                 Model 1              Model 2
---------------------------------------------------------
kappa1              -1.03 (0.05) ***     -1.96 (0.09) ***
kappa2               0.41 (0.04) ***      0.88 (0.06) ***
sigma1               2.56 (0.13) ***      1.04 (0.05) ***
sigma2               2.07 (0.06) ***      1.05 (0.03) ***
sigma3               2.91 (0.11) ***      1.17 (0.04) ***
rho1                                      0.17 (0.14)
rho2                                      0.35 (0.06) ***
rho3                                      0.37 (0.11) ***
s_xs1                                     0.94 (0.06) ***
s_xs2                                     1.50 (0.07) ***
o1_(Intercept)       0.78 (0.21) ***      0.99 (0.14) ***
o1_xo1                                    2.05 (0.09) ***
o1_xo2                                    1.01 (0.07) ***
o2_(Intercept)       0.82 (0.09) ***      0.96 (0.05) ***
o2_xo1                                   -0.99 (0.04) ***
o2_xo2                                    1.55 (0.04) ***
o3_(Intercept)       1.16 (0.16) ***      1.00 (0.09) ***
o3_xo1                                    1.58 (0.06) ***
o3_xo2                                   -1.92 (0.05) ***
---------------------------------------------------------
AIC                6601.95              4070.83
BIC                6641.21              4164.08
Log Likelihood    -3292.97             -2016.41
Pseudo R^2 (EL)       0.09                 0.51
Pseudo R^2 (MS)      -0.00                 0.46
R^2 (total)           0.00                 0.82
R^2 (1)              -0.00                 0.84
R^2 (2)              -0.00                 0.76
R^2 (3)              -0.00                 0.85
Num. obs.          1000                 1000
=========================================================
*** p < 0.001; ** p < 0.01; * p < 0.05
```

Finally, the key interest of an OPSR study almost certainly is the estimation of treatment effects which relies on (counterfactual) conditional expectations as already noted in the mathematical exposition.

```
R> p1 <- predict(fit, group = 1, type = "response")
R> p2 <- predict(fit, group = 1, counterfact = 2, type = "response")
```

where `p1` is the result of applying Equation 6.7 and `p2` is the counterfactual outcome resulting from Equation 6.8. The following `type` arguments are available

- `type = "response"`: Predicts the continuous outcome according to the Equations referenced above.
- `type = "unlog-response"`: Predicts the back-transformed response according to Equations 6.9–6.10 if the continuous outcome was log-transformed (either in the `formula` or during data pre-processing). The smoothing constant used during the continuity correction (i.e., the δ in $y_j = \ln(Y_j + \delta)$) can be specified via the `delta` argument and defaults to 1.
- `type = "prob"`: Returns the probability vector of belonging to `group`.
- `type = "mills"`: Returns the "inverse Mills ratio".
- `type = "correction"`: Returns $\rho_j \sigma_j$IMR respectively $\rho_{j'} \sigma_{j'}$IMR (if `counterfact = j'` was specified) from Equation 6.7 or 6.8.
- `type = "Xb"`: Returns $\boldsymbol{X}_j \boldsymbol{\beta}_j$ respectively $\boldsymbol{X}_{j'} \boldsymbol{\beta}_{j'}$ (if `counterfact = j'` was specified) from Equation 6.7 or 6.8.

Elements are `NA_real_` if the `group` does not correspond to the observed regime. This ensures consistent output length.

Now that the user understands the basic workflow, we illustrate some nuances by reproducing a key output of Wang and Mokhtarian (2024) where they investigate the treatment effect of telework (TW) on weekly vehicle miles driven. The data is attached, documented (`?telework_data`) and can be loaded by

```
R> data("telework_data", package = "OPSR")
```

The final model specification reads

```
R> f <-
+    twing_status | vmd_ln ~
+    edu_2 + edu_3 + hhincome_2 + hhincome_3 + flex_work + work_fulltime +
+    twing_feasibility + att_proactivemode + att_procarowning + att_wif +
+    att_proteamwork + att_tw_effective_teamwork + att_tw_enthusiasm +
+    att_tw_location_flex |
+    female + age_mean + age_mean_sq + race_black + race_other + vehicle +
+    suburban + smalltown + rural + work_fulltime + att_prolargehouse +
```

```
+    att_procarowning + region_waa |
+    edu_2 + edu_3 + suburban + smalltown + rural + work_fulltime +
+    att_prolargehouse + att_proactivemode + att_procarowning |
+    female + hhincome_2 + hhincome_3 + child + suburban + smalltown +
+    rural + att_procarowning + region_waa
```

and the model can be estimated by

```
R> start_default <- opsr(f, telework_data, .get2step = TRUE)
R> fit <- opsr(f, telework_data, start = start, method = "NM",
+    iterlim = 50e3, printLevel = 0)
```

where we demonstrate that

1. Default starting values as computed by the Heckman two-step procedure can be retrieved (`.get2step = TRUE`).

2. `start` values can be overridden (we have hidden the `start` vector here for brevity). If the user wishes to pass start values manually, some minimal conventions have to be followed as documented in `?opsr_check_start`.

3. Alternative maximization methods (here "Nelder-Mead"; `method = "NM"`) can be used (as in the original paper).

With help of the **texreg** package, production-grade tables (in various output formats) can be generated with ease.

```
R> texreg::texreg(
+    fit, beside = TRUE, include.R2 = TRUE, include.pseudoR2 = TRUE,
+    custom.model.names = custom.model.names, groups = groups,
+    custom.coef.names = custom.coef.names, scalebox = 0.73,
+    booktabs = TRUE, dcolumn = TRUE, no.margin = TRUE,
+    use.packages = FALSE, float.pos = "htbp", single.row = TRUE,
+    caption = "Replica of \\citet{Wang+Mokhtarian:2024}, Table 3.",
+    label = "tab:wang-replica",
+    custom.note = custom.note
+  )
```

Dot arguments (`...`) passed to `texreg()` (or similar functions) are forwarded to a S4 method `extract()` which extracts the variables of interest from a model fit (see also `?extract.opsr`). We demonstrate here that

1. The model components can be printed side-by-side (`beside = TRUE`).

	Structural	Selection	NTWer (535)	NUTWer (322)	UTWer (727)
Kappa 1	1.23 (0.17)***				
Kappa 2	2.46 (0.18)***				
Sigma 1	1.18 (0.05)***				
Sigma 2	1.23 (0.07)***				
Sigma 3	1.43 (0.04)***				
Rho 1	0.05 (0.10)				
Rho 2	0.13 (0.07)				
Rho 3	0.30 (0.07)***				
Education (ref: high school or less)					
Some college		0.32 (0.14)*		0.15 (0.33)	
Bachelor's degree or higher		0.47 (0.13)***		0.62 (0.32)*	
Household income (ref: <$50,000)					
$50,000 to $99,999		0.06 (0.12)			0.47 (0.23)*
$100,000 or more		0.25 (0.11)*			0.31 (0.23)
Flexible work schedule		0.31 (0.10)**			
Full time worker		0.33 (0.10)**	0.45 (0.13)***	0.69 (0.17)***	
Teleworking feasibility		0.13 (0.01)***			
Attitudes					
Pro-active-mode		0.08 (0.04)*		−0.18 (0.08)*	
Pro-car-owning		−0.08 (0.04)*	0.14 (0.07)*	0.16 (0.09)	0.25 (0.06)***
Work interferes with family		0.11 (0.04)**			
Pro-teamwork		0.09 (0.04)*			
TW effective teamwork		0.32 (0.04)***			
TW enthusiasm		0.09 (0.04)*			
TW location flexibility		0.08 (0.04)*			
Intercept			3.64 (0.27)***	2.49 (0.37)***	2.38 (0.26)***
Female			−0.21 (0.10)*		−0.36 (0.11)***
Age			0.01 (0.00)*		
Age squared			−0.00 (0.00)		
Race (ref: white)					
Black			−0.40 (0.24)		
Other races			−0.06 (0.18)		
Number of vehicles			0.12 (0.05)*		
Residential location (ref: urban)					
Suburban			0.07 (0.15)	0.45 (0.17)**	0.28 (0.14)*
Small town			0.47 (0.18)**	0.19 (0.29)	0.29 (0.28)
Rural			0.60 (0.23)**	0.81 (0.31)**	0.88 (0.34)**
Pro-large-house			0.18 (0.05)***	0.18 (0.08)*	
Region indicator (WAA)			−0.25 (0.11)*		−0.27 (0.11)*
Number of children					0.18 (0.06)**
AIC	7191.35				
BIC	7491.94				
Log Likelihood	−3539.67				
Pseudo R^2 (EL)	0.49				
Pseudo R^2 (MS)	0.46				
R^2 (total)	0.24				
R^2 (1)	0.18				
R^2 (2)	0.18				
R^2 (3)	0.12				
Num. obs.	1584				

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

TABLE 6.1: Replica of Wang and Mokhtarian (2024), Table 3.

2. Additional goodness-of-fit indicators can be included (`include.R2 = TRUE` and `include.pseudoR2 = TRUE`).

3. The output formatting can be controlled flexibly, by reordering, renaming and grouping coefficients (the fiddly but trivial details are hidden here for brevity).

6.3.2 *Tobit-5 model and comparison to* **sampleSelection**

As noted in Section 6.1, the Tobit-5 model can be seen as a form of OPSR with only two selection outcomes and can be fitted with the R-package **sampleSelection**. In this section, we illustrate that **OPSR** can estimate Tobit-5 models (as all the other examples involve three regimes) and that the results match the ones obtained with **sampleSelection**. The example, using simulated data, is directly taken from the vignette Toomet and Henningsen (2020, Section 4.2) `vignette("selection", package = "sampleSelection")`.

We create the following switching regression problem

```
R> set.seed(0)
R> vc <- diag(3)
R> vc[lower.tri(vc)] <- c(0.9, 0.5, 0.1)
R> vc[upper.tri(vc)] <- vc[lower.tri(vc)]
R> eps <- rmvnorm(500, c(0, 0, 0), vc)
R> xs <- runif(500)
R> ys <- xs + eps[, 1] > 0
R> xo1 <- runif(500)
R> yo1 <- xo1 + eps[, 2]
R> xo2 <- runif(500)
R> yo2 <- xo2 + eps[, 3]
R> yo <- ifelse(ys, yo2, yo1)
R> ys <- as.numeric(ys) + 1
R> dat <- data.frame(ys, yo, yo1, yo2, xs, xo1, xo2)
R> head(dat)
```

```
  ys       yo      yo1     yo2    xs    xo1    xo2
1  2  2.34301  0.99101  2.3430 0.531 0.5724 0.6716
2  2 -0.89646  1.75863 -0.8965 0.802 0.5999 0.1878
3  1  0.00931  0.00931  0.2238 0.479 0.7945 0.5048
4  2 -0.01742  2.57710 -0.0174 0.177 0.5046 0.0273
5  1 -0.35597 -0.35597 -0.1317 0.397 0.5402 0.4963
6  2 -0.03943  0.02728 -0.0394 0.814 0.0241 0.9474
```

Using **sampleSelection**, the estimation call reads

```
R> tobit5_s <- selection(ys ~ xs, list(yo1 ~ xo1, yo2 ~ xo2), data = dat)
R> summary(tobit5_s)

--------------------------------------------
Tobit 5 model (switching regression model)
Maximum Likelihood estimation
Newton-Raphson maximisation, 11 iterations
Return code 1: gradient close to zero (gradtol)
Log-Likelihood: -896
500 observations: 172 selection 1 (1) and 328 selection 2 (2)
10 free parameters (df = 490)
Probit selection equation:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   -0.155      0.105   -1.47     0.14
xs             1.141      0.179    6.39  3.9e-10 ***
Outcome equation 1:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   0.0271     0.1640    0.17     0.87
xo1           0.8396     0.1497    5.61  3.4e-08 ***
Outcome equation 2:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)    0.158      0.188    0.84      0.4
xo2            0.838      0.171    4.91  1.3e-06 ***
   Error terms:
       Estimate Std. Error t value Pr(>|t|)
sigma1   0.9319     0.0921   10.12   <2e-16 ***
sigma2   0.9070     0.0443   20.45   <2e-16 ***
rho1     0.8899     0.0535   16.62   <2e-16 ***
rho2     0.1770     0.3314    0.53     0.59
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
--------------------------------------------
```

which is equivalent to **OPSR**

```
R> tobit5_o <- opsr(ys | yo ~ xs | xo1 | xo2, data = dat, printLevel = 0)
R> summary(tobit5_o)

Call:
opsr(formula = ys | yo ~ xs | xo1 | xo2, data = dat, printLevel = 0)

BFGS maximization, 67 iterations
Return code 0: successful convergence
Runtime: 0.0498 secs
```

```
Number of regimes: 2
Number of observations: 500 (172, 328)
Estimated parameters: 10

Log-Likelihood: -896
AIC: 1812
BIC: 1854
Pseudo R-squared (EL): 0.122
Pseudo R-squared (MS): 0.054
Multiple R-squared: 0.336 (0.247, 0.069)

Estimates:
                Estimate Std. error t value Pr(> t)
kappa1            0.1550     0.1047    1.48    0.14
s_xs              1.1408     0.1792    6.37 1.9e-10 ***
o1_(Intercept)    0.0271     0.1692    0.16    0.87
o1_xo1            0.8396     0.1453    5.78 7.6e-09 ***
o2_(Intercept)    0.1583     0.2129    0.74    0.46
o2_xo2            0.8375     0.1669    5.02 5.2e-07 ***
sigma1            0.9319     0.0949    9.82 < 2e-16 ***
sigma2            0.9070     0.0472   19.20 < 2e-16 ***
rho1              0.8899     0.0515   17.27 < 2e-16 ***
rho2              0.1768     0.3848    0.46    0.65
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Wald chi2 (null): 100 on 3 DF, p-value: < 0
Wald chi2 (rho): 298 on 2 DF, p-value: < 0
```

6.4 CASE STUDY

Now, that the reader is familiar with the main functionality of **OPSR**, this section demonstrates how to employ it in a real-world example. The emphasis, therefore, lies not on what each function does but on guiding the reader through the modeling and post-estimation steps. We investigate telework treatment effects on weekly distance traveled (aggregated over all modes of transport). This contrasts Wang and Mokhtarian (2024) who used vehicle miles driven (i.e., car only).

We first discuss the model building strategy to arrive at an appropriately specified OPSR model. The OPSR model is then compared to a model not accounting for error correlation and implications for treatment effects are shown. The case study concludes with a discussion on unit treatment effects investigating to what degree teleworking influence total travel demand across all modes.

We use the TimeUse+ dataset (Winkler *et al.*, 2024), a smartphone-based diary, recording travel, time use, and expenditure data. Our analytical sample comprises employed individuals and is based on what Winkler and Axhausen (2024) identified as valid days. A valid day has at least 20 hours of information where 70% of the events were validated by the user. Users who did not have at least 14 valid days were excluded. For the remaining 824 participants mobility indicators for a typical week were constructed. The telework status is based on tracked (and labelled) work activities and three regimes are differentiated: Non-teleworkers (NTWers), Non-usual teleworkers (NUTWers; <3 days/week) and Usual teleworkers (UTWers; 3+ days/week).

The data, underlying this analysis, is attached, documented (`?timeuse_data`) and can be loaded by

```
R> data("timeuse_data", package = "OPSR")
```

A basic boxplot of the response variable against the three telework statuses is displayed in Figure 6.1. By simply looking at the data descriptively, we might prematurely conclude that telework does not impact weekly distance traveled. However, the whole value proposition of OPSR (and switching regression models in general) lies in estimating treatment effects by generating conterfactuals that are otherwise unobservable in cross-sectional datasets. If the teleworkers self-select, the counterfactual is not simply the group average of the non-teleworkers. More prosaically, if UTWers stopped teleworking, they might travel more or less than the actual NTWers. And as discussed, this might stem from both observable as well as unobservable factors. Meanwhile, UTWers have the highest average commute distance, followed by NUTWers and NTWers.

As mentioned in Section 6.2, the analyst needs to think of an identification restriction: In our application, we reserve the international standard classification of occupations (ISCO-08) variables for the selection process. To simplify model specification, we first estimate the ordered probit model separately, using `polr()` from the **MASS** package (Venables and Ripley, 2002). It should be noted here, that the resulting parameter estimates of the selection process are unbiased.

```
R> drop <- c("id", "weekly_km", "log_weekly_km", "commute_km",
+    "log_commute_km", "wfh_days")
```

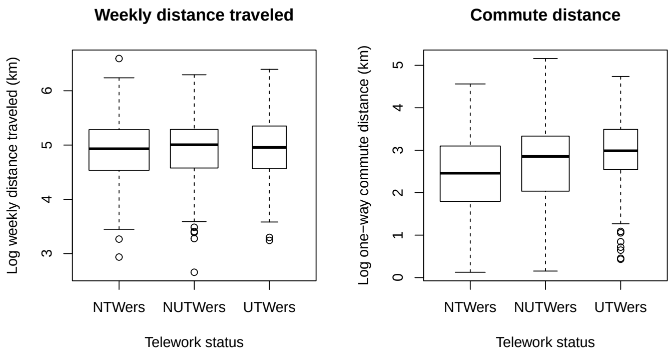

FIGURE 6.1: Log weekly distance traveled and log one-way commute distance for different telework statuses.

```
R> dat_polr <- subset(timeuse_data, select = !(names(timeuse_data) %in% drop))
R> dat_polr$wfh <- factor(dat_polr$wfh)
R> fit_polr <- MASS::polr(wfh ~ ., dat_polr, method = "probit")
```

The `stepAIC()` function chooses a selection model specification by AIC in a stepwise algorithm.

```
R> fit_step <- MASS::stepAIC(fit_polr, trace = FALSE)
R> fit_step$anova

Stepwise Model Path
Analysis of Deviance Table

Initial Model:
wfh ~ start_tracking + age + car_access + dogs + driverlicense +
    educ_higher + fixed_workplace + grocery_shopper + hh_income +
    hh_size + isco_clerical + isco_craft + isco_elementary +
    isco_managers + isco_plant + isco_professionals + isco_service +
    isco_agri + isco_tech + married + n_children + freq_onl_order +
    parking_home + parking_work + permanent_employed + rents_home +
    res_loc + sex_male + shift_work + swiss + vacation + workload +
    young_kids

Final Model:
wfh ~ age + car_access + educ_higher + fixed_workplace + grocery_shopper +
    hh_income + isco_clerical + isco_craft + isco_elementary +
    isco_tech + freq_onl_order + parking_home + permanent_employed +
```

```
    shift_work + workload + young_kids


                  Step Df Deviance Resid. Df Resid. Dev  AIC
1                                        778       1429 1521
2      - start_tracking  6   2.0260       784       1431 1511
3             - res_loc  3   2.8697       787       1434 1508
4       - isco_managers  1   0.0133       788       1434 1506
5           - isco_agri  1   0.0415       789       1434 1504
6            - vacation  1   0.1212       790       1434 1502
7       - driverlicense  1   0.2959       791       1434 1500
8            - sex_male  1   0.5118       792       1435 1499
9          - n_children  1   0.4769       793       1435 1497
10            - hh_size  1   0.4137       794       1436 1496
11            - married  1   0.3909       795       1436 1494
12       - isco_service  1   0.4773       796       1437 1493
13         - isco_plant  1   0.6176       797       1437 1491
14         - rents_home  1   1.2327       798       1438 1490
15       - parking_work  1   1.1424       799       1440 1490
16              - swiss  1   1.5091       800       1441 1489
17               - dogs  1   1.8158       801       1443 1489
18 - isco_professionals  1   1.8728       802       1445 1489
```

The resulting selection process specification can then be passed to `opsr()`, along with a common (or separate) process specification for the outcome processes. **OPSR** recognizes potential identification problems (e.g., colinear variables or missing factor levels in one of the groups), raises a warning if such problems arise and fixes the causing coefficients at 0. Through this process, we have identified two singularity issues for the UTWers: First, `shift_work` is a constant and second, `parking_home` is colinear with `car_access`.

We then follow the conventional (somewhat heuristic) model building strategy to specify the full identified model and then exclude all variables that do not produce significant estimates (at the 10% level). The formula specification of the full model is hidden here for brevity.

```
R> fit_full <- opsr(f_full, timeuse_data, printLevel = 0)
R> f_red <- wfh | log_weekly_km ~
+    age + educ_higher + hh_income + young_kids + workload + fixed_workplace +
+    shift_work + permanent_employed + isco_craft + isco_tech + isco_clerical +
+    isco_elementary + car_access + parking_home + freq_onl_order +
+    grocery_shopper |
+    sex_male + res_loc + workload + permanent_employed + parking_work |
```

```
+    swiss + res_loc + young_kids + workload + parking_work |
+    sex_male + swiss + fixed_workplace + permanent_employed + parking_work
R> fit_red <- opsr(f_red, timeuse_data, printLevel = 0)
R> print(anova(fit_red, fit_full), print.formula = FALSE)

Likelihood Ratio Test

   logLik      Df    Test Restrictions Pr(>Chi)
1 -1337.0    50.0
2 -1316.8    99.0    40.4           49      0.8

R> summary(fit_red)

Call:
opsr(formula = f_red, data = timeuse_data, printLevel = 0)

BFGS maximization, 234 iterations
Return code 0: successful convergence
Runtime: 1.45 secs
Number of regimes: 3
Number of observations: 824 (424, 265, 135)
Estimated parameters: 50

Log-Likelihood: -1337
AIC: 2774
BIC: 3010
Pseudo R-squared (EL): 0.202
Pseudo R-squared (MS): 0.126
Multiple R-squared: 0.214 (0.201, 0.189, 0.289)

Estimates:
                       Estimate Std. error t value Pr(> t)
kappa1                  0.13345    0.40919    0.33 0.74433
kappa2                  1.25047    0.40781    3.07 0.00217 **
s_age                   0.00725    0.00403    1.80 0.07219 .
s_educ_higher           0.44929    0.09295    4.83 1.3e-06 ***
s_hh_income4001_8000   -1.06428    0.25627   -4.15 3.3e-05 ***
s_hh_income8001_12000  -0.89366    0.25137   -3.56 0.00038 ***
s_hh_income12001_16000 -0.72192    0.26184   -2.76 0.00583 **
s_hh_income16001+      -0.69387    0.28776   -2.41 0.01590 *
s_hh_incomeNA          -0.63145    0.34501   -1.83 0.06722 .
s_young_kids            0.29617    0.10095    2.93 0.00335 **
s_workload              0.05353    0.02404    2.23 0.02598 *
s_fixed_workplace      -0.55419    0.14298   -3.88 0.00011 ***
```

```
s_shift_work           -0.82518    0.16677   -4.95 7.5e-07 ***
s_permanent_employed    0.33270    0.18560    1.79 0.07305 .
s_isco_craft           -0.67913    0.22364   -3.04 0.00239 **
s_isco_tech             0.21921    0.13246    1.65 0.09794 .
s_isco_clerical         0.55330    0.09817    5.64 1.7e-08 ***
s_isco_elementary      -4.46545    1.29525   -3.45 0.00057 ***
s_car_access           -0.71446    0.26447   -2.70 0.00690 **
s_parking_home          0.64134    0.25170    2.55 0.01083 *
s_freq_onl_order        0.20944    0.08812    2.38 0.01747 *
s_grocery_shopper      -0.13267    0.08788   -1.51 0.13116
o1_(Intercept)          3.90114    0.17240   22.63 < 2e-16 ***
o1_sex_male             0.09334    0.05623    1.66 0.09691 .
o1_res_locrural         0.21702    0.09467    2.29 0.02188 *
o1_res_locsuburban      0.10923    0.09818    1.11 0.26593
o1_res_locurban        -0.01088    0.10899   -0.10 0.92049
o1_workload             0.06058    0.01314    4.61 4.0e-06 ***
o1_permanent_employed   0.29905    0.11690    2.56 0.01052 *
o1_parking_work         0.23222    0.05204    4.46 8.1e-06 ***
o2_(Intercept)          3.88702    0.21570   18.02 < 2e-16 ***
o2_swiss                0.18517    0.10900    1.70 0.08935 .
o2_res_locrural         0.43405    0.14799    2.93 0.00336 **
o2_res_locsuburban      0.22649    0.14363    1.58 0.11482
o2_res_locurban         0.17387    0.16409    1.06 0.28933
o2_young_kids          -0.15630    0.06958   -2.25 0.02469 *
o2_workload             0.07455    0.01515    4.92 8.7e-07 ***
o2_parking_work         0.16130    0.07033    2.29 0.02182 *
o3_(Intercept)          3.85223    0.33710   11.43 < 2e-16 ***
o3_sex_male             0.23879    0.08908    2.68 0.00735 **
o3_swiss                0.39109    0.12054    3.24 0.00118 **
o3_fixed_workplace     -0.36832    0.12432   -2.96 0.00305 **
o3_permanent_employed   0.54238    0.25706    2.11 0.03487 *
o3_parking_work         0.28905    0.09202    3.14 0.00168 **
sigma1                  0.51246    0.02225   23.04 < 2e-16 ***
sigma2                  0.54030    0.02954   18.29 < 2e-16 ***
sigma3                  0.54263    0.05799    9.36 < 2e-16 ***
rho1                    0.28712    0.19141    1.50 0.13360
rho2                   -0.18889    0.14349   -1.32 0.18804
rho3                    0.46193    0.22531    2.05 0.04034 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Wald chi2 (null): 2584 on 39 DF, p-value: < 0
Wald chi2 (rho): 8.93 on 3 DF, p-value: < 0.03
```

The reduced model specification (`fit_red`) is not rejected in the likelihood ratio test. Further, there is significant error correlation between the selection process and the outcome process for the UTWers (`rho3`). The Wald-test suggests that the null hypothesis (`rho1` = `rho2` = `rho3` = 0) can be rejected at the 5% level, suggesting that OPSR is beneficial given our model assumptions.

We first define some helper functions to compute treatment effects

- `estimated_weekly_km()`: Computes all possible factual and counterfactual conditional expectations (for each `group` and `counterfact` tuple).
- `average()`: Averages the conditional expectations from the previous step.
- `pairwise_diff()`: The treatment effect is then the pairwise difference of these averaged conditional expectations.
- `te()`: Computes the treatment effect from an '`opsr`' fit object by combining all the steps above.

Unless otherwise mentioned, we use the `fit_red` model in the remainder.

```
R> tw_status <- c("NTW", "NUTW", "UTW")
R> estimated_weekly_km <- function(object, type = "unlog-response") {
+    nReg <- object$nReg
+    out <- vector("list", nReg)
+    counterfacts <- vector("list", nReg)
+    for (g in 1:nReg) {
+      for (c in 1:nReg) {
+        counterfacts[[c]] <- predict(object, group = g, counterfact = c,
+          type = type)
+      }
+      df <- as.data.frame(counterfacts)
+      names(df) <- tw_status
+      out[[g]] <- df
+    }
+    names(out) <- tw_status
+    out
+  }
R> average <- function(object) {
+    ae <- lapply(object, function(x) {
+      apply(x, 2, function(x) mean(x, na.rm = TRUE))
+    })
+    as.data.frame(ae)
```

```
+ }
R> pairwise_diff <- function(mat) {
+   n <- nrow(mat)
+   m <- ncol(mat)
+   result <- matrix(NA, nrow = n, ncol = m)
+   for (j in 1:m) {
+     result[, j] <- c(
+       mat[2, j] - mat[1, j],
+       mat[3, j] - mat[1, j],
+       mat[3, j] - mat[2, j]
+     )
+   }
+   rownames(result) <-
+     c("NTWing -> NUTWing", "NTWing -> UTWing", "NUTWing -> UTWing")
+   colnames(result) <- c("NTWer", "NUTWer", "UTWer")
+   result
+ }
R> te <- function(object) {
+   awk <- average(estimated_weekly_km(object))
+   te <- pairwise_diff(awk)
+   te
+ }
R> te(fit_red)
```

```
                  NTWer NUTWer UTWer
NTWing -> NUTWing  37.7  -10.6 -54.2
NTWing -> UTWing  -54.7  -47.0 -44.3
NUTWing -> UTWing -92.4  -36.4   9.9
```

Telework reduces weekly kilometers traveled across all groups, with the exception of NTWers who would be more mobile when switching from NTWing to NUTWing (37.74 km; column `NTWer`, row `NTWing -> NUTWing`) and UTWers who would travel more when further adopting telework from NUTWing (9.9 km). The treatment effects when switching from NTWing to NUTWing are strongest for UTWers (-54.22 km) compared to NTWers (37.74 km) and NUTWers (-10.58 km). Treatment effects for NTWing to UTWing are similar across all three groups, slightly stronger for NTWers (-54.7 km). Interestingly, NTWers show a non-linear pattern, first increasing weekly kilometers when adopting some telework (37.74 km; NTWing to NUTWing) but then substantially decreasing weekly kilometers with more telework (-92.44 km; NUTWing to UTWing). An explanation could be, that these individuals (living closer to their workplace) do initially not adjust activity chains and location choices when only occasionally teleworking.

For example, an individual might stay subscribed to the gym close to the workplace and visit that facility even on a home office day. On the other hand, UTWers show exactly an inverse pattern, first (NTWing to NUTWing) strongly reducing weekly kilometers (-54.22 km) but upon further telework adoption (NUTWing to UTWing) only minimally adjusting weekly kilometers (9.9 km). A similar argument could be made, that these individuals (living further from their workplace) already from the start adjust activity chains and location choices. One can therefore conclude, that the treatment effect over the full range (NTWing to UTWing) is similar across all groups but the main travel reduction happens at different treatment intensities. Figure 6.2 (panel d) visualizes these treatment effects and shows the linear pattern for NUTWers and the (mirrored) hockey stick pattern for NTWers and UTWers.

While the discussion above was based on averaged group-level treatment effects, Figure 6.2 shows the distributions of predicted weekly distance traveled by teleworker group. Each panel presents a pair of (un)treated telework statuses as the margins and the dashed lines are the empirical sample means. The solid black reference line marks the instances where weekly distance traveled is equal for both of the paired (un)treated telework statuses. I.e., points below the reference line indicate more travel under the regime depicted on the x-axis.

Model	Parent	Error correlation	Description
`fit_full`		•	Full identified model, including all variables as linear effects
`fit_red`	`fit_full`	•	Excluding all variables not significant at the 10% level
`fit_nocor`	`fit_red`	◦	Fixing the `rho` coefficients at 0

TABLE 6.2: Model overview. The model is based on *Parent* as elaborated under *Description*.

We now demonstrate, that not controlling for error correlation leads to different and most likely wrong conclusions, since parameter estimates might be biased. We derive a model (`fit_nocor`) without error correlation by setting the `rho` coefficients to 0. I.e., this is the same as separately estimating an ordered probit model and three linear regression models.

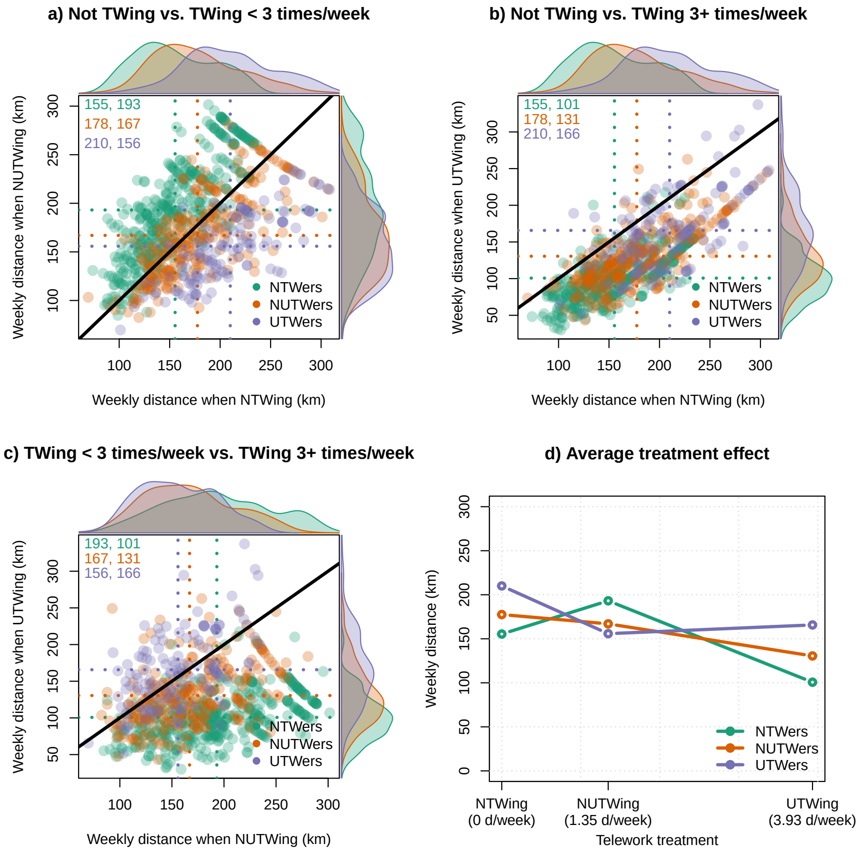

FIGURE 6.2: Treatment effects.

```
R> start <- coef(fit_red)
R> fixed <- c("rho1", "rho2", "rho3")
R> start[fixed] <- 0
R> fit_nocor <- opsr(f_red, timeuse_data, start = start, fixed = fixed,
+    printLevel = 0)
```

The treatment effects are

```
R> te(fit_red)

                    NTWer NUTWer UTWer
NTWing -> NUTWing   37.7  -10.6 -54.2
```

```
NTWing -> UTWing  -54.7  -47.0 -44.3
NUTWing -> UTWing -92.4  -36.4   9.9

R> te(fit_nocor)

                  NTWer NUTWer UTWer
NTWing -> NUTWing 17.72  14.14 14.55
NTWing -> UTWing   8.80  12.31  7.89
NUTWing -> UTWing -8.93  -1.83 -6.66
```

As we see, `fit_nocor` yields completely different insights, in particular, that telework generally increases weekly distance traveled, consistent with previous cross-sectional studies that did not account for self-selection bias (for studies indicating that telework increases travel demand, see Zhu and Mason, 2014; He and Hu, 2015; Kim *et al.*, 2015).

Lastly (using `fit_red`), we compute unit treatment effects and compare them to the average two-way commute distance for each group. The unit treatment effect is calculated by dividing the total treatment effect by the corresponding average teleworking frequency difference (`twdiff1` to `twdiff3` below). I.e., the treatment effect is standardized and therefore also comparable for different regime switching (e.g., NTWing to NUTWing vs. NUTWing to UTWing).

```
R> dat_ute <- subset(timeuse_data, select = c(commute_km, wfh, wfh_days))
R> dat_ute <- aggregate(cbind(wfh_days, 2 * commute_km) ~ wfh,
+    data = dat_ute, FUN = mean)
R> top <- t(dat_ute[2:3])
R> colnames(top) <- c("NTWers", "NUTWers", "UTWers")
R> rownames(top) <- c("WFH (days)", "2-way commute (km)")
R> i <- "WFH (days)"
R> twdiff1 <- top[i, "NUTWers"] - top[i, "NTWers"]
R> twdiff2 <- top[i, "UTWers"] - top[i, "NTWers"]
R> twdiff3 <- top[i, "UTWers"] - top[i, "NUTWers"]
R> twdiff <- matrix(
+    c(rep(twdiff1, 3), rep(twdiff2, 3), rep(twdiff3, 3)),
+    nrow = 3
+  )
R> bottom <- te(fit_red) / twdiff
R> ute <- rbind(top, bottom)
R> ute

                   NTWers NUTWers UTWers
WFH (days)            0.0    1.35   3.93
```

```
2-way commute (km)   30.1   43.33  51.07
NTWing -> NUTWing    28.0   -2.69 -20.97
NTWing -> UTWing    -40.6  -11.95 -17.14
NUTWing -> UTWing   -68.6   -9.26   3.83
```

Generally, telework reduces weekly distance traveled by less than the foregone commute distance, which indicates, that a rebound effect (compensating leisure travel) exists. For example, the NUTWers could save 43.33 km in commute travel but only reduce -2.69 km per marginal teleworking day when switching from NTWing to NUTWing. This compensating travel exists for all TW groups except the NTWers (NTWing to UTWing and NUTWing to UTWing), where we observe diminished travel activity beyond foregone commutes. The insights from the previous discussion on treatment effects carry over: Adjustments in weekly distance traveled are very different both across the three teleworker groups but also across the regime switching.

6.5 SUMMARY AND DISCUSSION

In a real-world setting, the treatment is usually not exogenously prescribed but self-selected. Various methods in various statistical environments exist to account for selection-bias which arises if unobserved factors simultaneously influence both the selection and outcome process. OPSR is introduced as a special case of endogenous switching regression to account selection biases for ordinal treatments (where the well-known Tobit-5 model is a special case of OPSR, i.e., with only two treatment regimes). The model frame for such Heckman-type models as well as their implementation in the R system for statistical computing is reviewed. The here presented R implementation in package **OPSR** re-uses design and functionality of the corresponding R software. Hence, the new function `opsr()` is straightforward to apply for model fitting and diagnostics. Further, it is fast and memory efficient thanks to the C++ implementation of the log-likelihood function which can also be parallelized. **OPSR** handles log-transformed outcomes which need special consideration when computing conditional expectations and thus treatment effects. In the case study, the OPSR method is applied to a tracking and activity diary dataset collected in Switzerland, investigating the telework treatment effects on weekly distance traveled across all modes. We demonstrate, first, how to specify an appropriate model and check for error correlation, and second, in how far computed treatment effects differ if the error correlation is not accounted for. We find that, overall, telework reduces travel. Non-teleworkers tend to have shorter commutes and adjust mobility patterns mainly when switching from non-usual telework to usual telework. On the other hand, weekly distance traveled slightly increases when initially adopting some telework. Contrary, usual teleworkers (had they not been teleworking) adjust mobility patterns strongly when adopting some telework but then only marginally adjust distance traveled when further adopting telework. Comparing the unit treatment effects to the two-way commute distance indicates that telework generally reduces weekly distance traveled and it does so by less than the foregone commute. Therefore, some compensating travel (rebound effects) exists for most of the teleworker groups.

7

ANALYSIS

All models are wrong, some are wronger!

The net effects of telework on transport demand are debated. We operationalize transport demand with weekly kilometers traveled and estimate treatment effects by employing ordered probit switching regression (OPSR), using the TimeUse+ tracking data. OPSR accounts for selection bias which may arise if unobserved factors simultaneously influence the treatment adoption (telework in our case) and the outcome. Our findings strengthen the narrative that telework reduces traveled distance and that small rebound effects can never offset forgone commutes by a wide margin. We estimate, that the travel reduction accounts to -16% comparing the current telework situation to the no telework reference. Unit treatment effects roughly correspond to the two-way commute distance. Our estimated treatment effects imply that travel reduction is much larger than simple group comparison would suggest. Further, we show that not accounting for self-selection potentially underestimates the true treatment effects quite substantially.

This chapter is based on the following paper

Heimgartner D. and K. W. Axhausen (2025) All Models are Wrong, Some Models are Wronger: On the Importance of Accounting for Self-Selection when Estimating Telework Treatment Effects, *Transportation Research Part B: Methodological*, submitted.

Author contributions

Study conception and design: all authors; analysis and interpretation of results: D. Heimgartner; original draft: D. Heimgartner; writing, reviewing and editing: all authors. All authors reviewed and approved the final manuscript.

The following changes were made

Most of the method section was already presented in Chapter 6 and was not repeated here for brevity. The Heckman-correction plot (originally in the appendix of the paper) was omitted as a similar plot is shown in Chapter 8.

7.1 INTRODUCTION

Researchers have long been interested in the relation between telework and transport demand (see Salomon 1986; Nilles 1988; Mokhtarian 1991 for early work). The obvious connection there, is, one less trip from the home to the office and (drumrolls) back. However, intricate potential adjustment channels such as induced travel due to increased time-flexibility or relocation and the acceptance for longer commutes open the door for counter-intuitive, yet interesting findings. Maybe not surprising, findings on telework's net benefits are mixed (Hook *et al.*, 2020). Wang and Mokhtarian (2024) even claim that scholarly work of the past decade leans to support evidence that telework induces more travel.

As intricate as the possible causal connections between telework and travel may be, as difficult it is to capture all of them in an integrated modeling framework. It is therefore easy to criticize simplifying assumptions (which could rule out some of the potential causal links). However, some simplifying assumptions are more necessary than others. Throughout econometric work the exogeneity of variables can easily be questioned – in the end "everything is endogenous". But in the telework literature, it is quite surprising, that a large body of literature is trying to model telework adoption and telework frequency, while the other body of literature uses the frequency as exogenous variable to explain travel behavior... We argue, that telework can be understood as a self-selected treatment and hence requires causal inference methods in spirit of Heckman: Selection bias may arise if unobserved factors influencing the treatment adoption also influence the outcome. "All models are wrong (that's why the ε is there) – some models are wronger."[1]

But before diving into a world of intricate error structures, we conduct descriptive analysis, showing various mobility indicators by telework status. We use the TimeUse+ dataset (Winkler *et al.*, 2024), a smartphone-based diary, recording travel, time use, and expenditure data and distinguish

1 Yes, "wronger" seems to be grammatically correct.

between two analytical perspectives: the disaggregate view and the aggregate view. The disaggregate view examines differences at the daily level by telework location, i.e., comparing telework days, hybrid (mixed) days, and office-based workdays. In contrast, the aggregate view focuses on broader group-level differences, comparing non-teleworkers, occasional teleworkers, and regular teleworkers. The disaggregate view is a very isolated view, falling short of unraveling overarching dependency patterns such as the implications of working from home over multiple days in a row, while the aggregate view is more of a medium-term view, incorporating adjustments once telework is more (or less) habitual.

With these two perspectives in mind, we tackle the following research questions: In how far do activity and mobility patterns differ between teleworkers and non-teleworkers on a particular day? In how far do current non-teleworkers, non-usual teleworkers and usual teleworkers differ in these activity and mobility patterns both on a daily basis as well as over a full workweek? The econometric part is then concerned with measuring the impact of telework on transport demand. Here, we operationalize transport demand by weekly kilometers traveled and formulate the following hypothesis: Telework treatment effects differ between the non-teleworkers, non-usual teleworkers and usual teleworkers (i.e., they have different factual and counterfactual weekly kilometers traveled). Telework reduces kilometers traveled, i.e., the foregone commute is not fully offset.

This paper can be seen as the third of a trilogy: The original paper by Wang and Mokhtarian (2024) recognizes methodological shortcomings in the telework-related program evaluation literature, proposes and employs the ordered probit endogenous switching regression (OPSR) model to correct for self-selection into a telework "regime" and estimates resulting treatment effects for weekly vehicle miles driven. Heimgartner and Wang (2025a) introduce the **OPSR** R-package and make the method widely available. This paper employs the method in the Swiss context and uses the aforementioned TimeUse+ dataset – based on tracked (rather than stated) telework episodes and travel metrics.

The remainder of the text is structured as follows: Section 7.2 reviews the literature. In Section 7.3 we describe the TimeUse+ dataset. Section 7.4 introduces the methods used, in particular the ordered probit switching regression model. In Section 7.5 we present the results, first descriptively for the disaggregate view, second for the aggregate view and third the model-implied results with an emphasize on treatment effects rather than behavioral implications of modeling parameters. Section 7.6 concludes.

7.2 LITERATURE REVIEW

This study builds on three key literature streams: Modeling telework frequency, its impact on transport demand and systemic consequences, and program evaluation for estimating treatment effects.

7.2.1 *Modeling telework frequency*

Early studies focused primarily on telework adoption, with interest gradually shifting to understand telework frequency. Common approaches include multinomial logit, ordered logit, and probit models, understanding frequency as count (Singh *et al.*, 2013) or as an ordinal scale (Shabanpour *et al.*, 2018). Treatment of zero telework frequencies varies: Some include it within one process (Beck *et al.*, 2020), while others model adoption separately (Pouri and Bhat, 2003) or even propose multiple (conditional) processes that manifest in a final frequency outcome (e.g. Singh *et al.*, 2013, who differentiate option, choice/adoption and frequency).

Employer-employee interactions remain understudied. Many studies use job attributes as proxies for employer constraints (Asmussen *et al.*, 2024). Heimgartner and Axhausen (2023e) investigate in how far preference and feasibility/employer constraints can be disentangled in an endogenous choice set formation approach while Mokhtarian and Salomon (1996) suggest directly incorporating such constraints into utility specifications.

7.2.2 *Systemic consequences of telework*

Research has long examined telework's impact on travel demand (for early work, see Salomon, 1986; Nilles, 1988; Mokhtarian, 1991). Early studies emphasized telecommuting's substitution effect (Pouri and Bhat, 2003), but net effects remain contested: Telework reduces commuting yet may induce additional travel due to increased flexibility, altered travel chains, or greater household vehicle use. Long-term effects include potential residential relocation and higher tolerance for longer commutes as found by Ravalet and Rérat (2019) and de Vos *et al.* (2018).

Maybe not surprisingly, findings on telework's impact on travel are mixed. Some studies show reduced personal kilometers traveled (Elldér, 2020), while others find increased trip distances, durations, and frequencies (Zhu, 2012). Chakrabarti (2018) report higher vehicle miles driven (VMD) for teleworkers, with occasional teleworkers traveling more than frequent ones.

Su *et al.* (2021) observe more complex travel schedules among teleworkers. A systematic review underscores these uncertainties in telework's net effects on travel and energy use (Hook *et al.*, 2020). As summarised in the literature review by Wang and Mokhtarian (2024), scholarly work of the past decade leans to support evidence that telework induces more travel.

7.2.3 *Program evaluation and selection bias*

Program evaluation estimates treatment effects by comparing "treated" to "untreated" groups. While experimental settings allow randomization, observational studies face selection bias when unobserved factors influence both treatment and outcomes (Heckman, 1979). This casts doubt on whether the previously discussed group-comparisons (between teleworkers and non-teleworkers) are even relevant to investigate net effects.

Various methods address selection bias: Difference-in-differences is used for longitudinal data, while cross-sectional approaches include instrumental variables, propensity score matching, regression discontinuity, and endogenous switching regression (ESR) models. ESR accounts for both selection on observables and unobservables in spirit of Heckman (Wang and Mokhtarian, 2024).

Heckman (1979) introduces a probit selection equation alongside a continuous outcome equation. A key extension is switching regression, which estimates separate outcome processes for different groups (introduced as the Roy model in Cameron and Trivedi 2005, or the Tobit 5 model in Amemiya 1985). Conditional mixed-process models generalize this framework for various outcome types (Roodman, 2011).

This study applies an ordered probit switching regression (OPSR) model, which handles ordered treatments and continuous outcomes (Chiburis and Lokshin, 2007). The **OPSR** R-package (Heimgartner and Wang, 2025a) makes modeling both fast and easy.

The paper most relevant for this study is the one by Wang and Mokhtarian (2024) as it proposes to employ OPSR to evaluate the telework program with regard to its implications for transport behavior. They use stated-preference data (unlike this study, but as most other work) and investigate the impact of telework on weekly VMD. They find that adopting teleworking at a high frequency level or increasing telework frequency from low to high levels (i.e., 3+ days/week) always leads to a reduction in VMD on average.

Three key insights emerge: First, various models address telework frequency, with debates on employer constraints' role and how to embody them in the model. Second, telework's net impact on transport demand remains contested, with second-order effects potentially offsetting benefits such as reduced travel or energy consumption. Third, telework can be understood as a self-selected treatment and hence requires causal inference methods. OPSR is a promising approach for addressing these complexities, though fully integrated models may better capture long-term effects like relocation.

7.3 DATA

We use the TimeUse+ dataset (Winkler *et al.*, 2024), a smartphone-based diary, recording travel, time use, and expenditure data fielded between 2022-07-18 and 2023-02-09. Our analytical sample comprises employed individuals and the observational unit is a valid person work day for the disaggregate (daily) analysis. A valid day has at least 20 hours of activity or travel information and the daily work duration needs to be 2 hours or beyond. Days with "unusual" travel activity (total distance travelled beyond the upper whisker at 152 km) are discarded. The activity durations and travel times were then rescaled to arrive at aligned 24 hour diaries. This left us with 958 individuals and 11'742 person days. The study period covered summer, autumn and winter months with most days being recorded during autumn. We control for seasonality in our model.

As evident from Table 7.1 (column Unweighted), the TimeUse+ sample is biased towards car owners, higher educated individuals and public transport (PT) season ticket owners. To correct for the selective attrition during the survey and tracking study, we use case weights obtained by iterative proportional fitting using the **anesrake** R-package (Pasek, 2018). Marginals from the mobility and transport microcensus 2021 (MTMC21, ARE and BFS, 2024) were targeted, excluding telework related variables which were potentially still influenced by the pandemic when the MTMC21 was fielded. The weighted sample matches the census data very well, importantly, now also for car and PT season ticket ownership which are known to influence mobility behavior. The weights are not used in the descriptive analysis but are used in estimation and post-estimation to more validly generalize the results to the Swiss employed population.

For the aggregate (weekly) analysis, we require individuals to have at least five (not necessarily consecutive) valid tracking days which reduces the sample to 879 individuals. We then aggregate the different daily indicators

	MTMC21	TimeUse+ Unweighted	TimeUse+ Weighted
N	27558.00	958.00	958.00
Age (mean, sd)	43.85 (12.75)	43.31 (11.35)	43.10 (11.99)
Gender (n, %)	12957.94 (47.02)	447.00 (46.66)	443.29 (46.27)
Marital status (n, %)			
civil	124.54 (0.45)	5.00 (0.52)	8.05 (0.84)
divorced	2746.66 (9.97)	77.00 (8.04)	93.23 (9.73)
married	13821.16 (50.15)	517.00 (53.97)	471.62 (49.23)
married separated	24.01 (0.09)	15.00 (1.57)	15.76 (1.64)
single	10505.73 (38.12)	341.00 (35.59)	368.60 (38.48)
widowed	335.90 (1.22)	3.00 (0.31)	0.75 (0.08)
Residential location type (n, %)			
rural	4466.02 (16.21)	144.00 (15.03)	137.09 (14.31)
suburban	5913.86 (21.46)	216.00 (22.55)	227.69 (23.77)
urban	17178.12 (62.33)	598.00 (62.42)	593.22 (61.92)
Highest education (n, %)			
mandatory	2233.91 (8.15)	13.00 (1.36)	65.00 (6.79)
secondary	12180.45 (44.43)	476.00 (49.69)	429.65 (44.85)
higher	13002.10 (47.42)	469.00 (48.96)	463.35 (48.37)
Household income (n, %)			
0 - 4000 CHF	1597.99 (6.90)	57.00 (6.16)	62.07 (6.72)
4001 - 8000 CHF	7884.58 (34.05)	305.00 (32.97)	305.30 (33.04)
8001 - 12000 CHF	7230.46 (31.22)	322.00 (34.81)	294.47 (31.87)
12001 - 16000 CHF	3559.20 (15.37)	156.00 (16.86)	143.76 (15.56)
16000+ CHF	2884.42 (12.46)	85.00 (9.19)	118.41 (12.82)
Household size (mean, sd)	2.68 (1.30)	2.77 (1.22)	2.67 (1.24)
Driver license (n, %)	25238.92 (91.59)	924.00 (96.45)	876.25 (91.47)
Car access (n, %)			
borrow	5632.37 (20.44)	109.00 (11.38)	201.48 (21.03)
no	4354.73 (15.80)	111.00 (11.59)	145.10 (15.15)
yes	17570.90 (63.76)	738.00 (77.04)	611.42 (63.82)
PT national season ticket (n, %)	2166.34 (7.87)	128.00 (13.36)	72.19 (7.54)
PT half-fare card (n, %)	9855.25 (35.78)	567.00 (59.19)	337.33 (35.21)
Works full time (n, %)	16006.63 (58.08)	550.00 (57.41)	602.60 (62.90)
Telework possible (n, %)	12887.46 (46.92)	521.00 (54.38)	496.92 (51.87)
Telework frequency (mean, sd)	1.99 (1.81)	1.64 (1.38)	1.67 (1.41)

Table 7.1: Sample comparison: TimeUse+ to the mobility and transport microcensus 2021.

(e.g., time spent on certain activities, kilometers traveled, number of trips, etc.) for a typical five-day work week.

The telework status is based on tracked work activities (both on home office and mixture days) and three regimes are differentiated: Non-teleworkers (NTWers; N=492), Non-usual teleworkers (NUTWers; <3 days/week; N=259) and Usual teleworkers (UTWers; $3+$ days/week; N=128). Throughout the text we use "TWing" to refer to the state and "TWers" to refer to the group (e.g., "Would UTWers switch to NTWing" implies that the current group of usual teleworkers would switch to a state of no teleworking). Weighted summary statistics for the three regimes are shown in Table 7.2. NUTWers work on average 1.28 days/week from home, while UTWers telework on average 3.59 days/week. Part-time work is more common among NUTWers (compared to UTWers). However, the full-time equivalent weekly hours worked are very similar across the three groups.

	Telework status		
	NTW	NUTW	UTW
N	506.94	223.56	132.89
Workload in % of full load	84.53 (23.22)	85.84 (22.17)	94.15 (13.98)
Hours worked h/week	39.72 (7.96)	43.03 (10.14)	49.61 (14.98)
Hours worked h/week, full-time equiv.*	51.20 (18.76)	53.75 (19.32)	54.63 (21.58)
Telework frequency d/week	0.00 (0.00)	1.28 (0.45)	3.59 (0.85)
Mixture days† d/week	0.00 (0.00)	1.69 (1.39)	1.57 (1.23)

*Normalized for workload; †Days worked both from home and the office

Table 7.2: Work-related summary statistics (mean, sd) by telework status (weighted).

Respondents were asked to state their typical weekly telework frequency (days/week) which we compare to the tracking-implied inferred frequency in Figure 7.1. We observe that the stated weekly frequencies do not fully align with observed behavior in particular for individuals stating that they are more frequent teleworkers. This hints that telework is used opportunistically and varies from one week to the other.

The socio-economic characteristics of the three teleworker groups are compared in Table 7.3. The means and standard deviations of the start month hint that the three groups are evenly represented over the course of the study and hence seasonality effects might influence mobility behaviour similarly across the three groups. Teleworkers (TWers) compared to NTWers

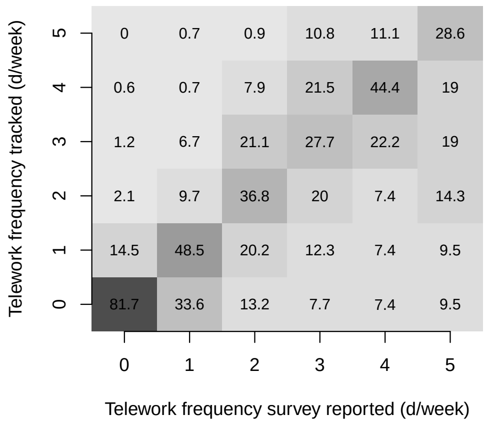

FIGURE 7.1: Comparing survey-reported telework frequencies to tracking-observed ones.

tend to be national PT season ticket owners, more highly educated, dog owners, frequent online shoppers but less frequent grocery shoppers, higher income, have children below the age of twelve (especially the NUTWers), managers or professionals, married, house or apartment owners and live in a more urban environment. Compared to NUTWers, UTWers tend to additionally have permanent work contracts but do not work in shifts. During the pandemic, the Swiss government enforced the duty to telework whenever possible. The telework frequency reported during such mandatory lockdowns is labeled teleworkability here and is expected to capture the (exogenous) telework suitability of a person's job.

7.4 METHODS

7.4.1 *Analysing state sequences*

The 24 hours of time-use can be seen as categorical activity-trip sequence data. We differentiate between seven activity types (chores/errands, leisure, self-care, sleep, travel, work and other) and discretize the day into 10 minute intervals which defines our state sequence.

	Telework status		
	NTW	NUTW	UTW
N	506.94	223.56	132.89
Start month (mean, sd)	9.82 (1.59)	9.73 (1.61)	9.73 (1.74)
Teleworkability (mean, sd)	1.41 (1.93)	3.19 (2.02)	4.62 (1.42)
Telework frequency (mean, sd)	0.00 (0.00)	1.28 (0.45)	3.59 (0.85)
Age (mean, sd)	42.38 (12.17)	44.58 (11.58)	43.07 (11.63)
Has dogs (n, %)	58.93 (11.62)	41.85 (18.72)	32.09 (24.15)
Higher education (n, %)	200.89 (39.63)	146.00 (65.31)	87.14 (65.57)
Frequent online shopper (n, %)	268.39 (52.94)	142.47 (63.73)	101.54 (76.41)
Grocery shopper (n, %)	246.93 (48.71)	90.41 (40.44)	40.13 (30.20)
Houesehold income (n, %)			
0 - 4000 CHF	38.90 (7.67)	8.91 (3.98)	9.29 (6.99)
4001 - 8000 CHF	192.14 (37.90)	59.83 (26.76)	22.29 (16.77)
8001 - 12000 CHF	164.08 (32.37)	70.28 (31.44)	39.52 (29.74)
12001 - 16000 CHF	77.01 (15.19)	39.61 (17.72)	19.23 (14.47)
16000+ CHF	34.81 (6.87)	44.92 (20.09)	42.57 (32.03)
Household size (mean, sd)	2.52 (1.25)	2.93 (1.15)	2.89 (1.35)
Married (n, %)	221.69 (43.73)	131.13 (58.66)	71.26 (53.62)
Number of children (mean, sd)	0.56 (0.93)	0.79 (1.00)	0.68 (0.97)
Parking home (n, %)	484.71 (95.62)	217.65 (97.36)	132.43 (99.66)
Parking work (n, %)	282.22 (55.67)	119.18 (53.31)	67.75 (50.98)
Tenant (n, %)	292.27 (57.66)	105.00 (46.97)	70.49 (53.05)
Residential location (n, %)			
rural	76.50 (15.09)	32.87 (14.70)	8.86 (6.66)
suburban	128.27 (25.30)	40.72 (18.22)	29.53 (22.22)
urban	302.17 (59.61)	149.96 (67.08)	94.50 (71.11)
Male (n, %)	257.09 (50.72)	125.70 (56.23)	73.94 (55.64)
Swiss (n, %)	416.55 (82.17)	178.33 (79.77)	103.84 (78.14)
Has kids below 12 (n, %)	102.12 (20.14)	74.53 (33.34)	33.26 (25.03)
Fixed workplace (n, %)	478.41 (94.37)	197.70 (88.43)	118.77 (89.37)
ISCO (n, %)			
agri, forest & fishery	1.90 (0.38)	2.11 (0.94)	4.34 (3.27)
clerical	102.09 (20.14)	76.24 (34.10)	40.06 (30.14)
craft & trades	49.97 (9.86)	4.66 (2.09)	1.82 (1.37)
elementary	7.28 (1.44)	0.00 (0.00)	0.00 (0.00)
managers	110.13 (21.72)	65.79 (29.43)	36.15 (27.20)
plant & machine	18.19 (3.59)	0.30 (0.13)	0.00 (0.00)
professionals	78.35 (15.46)	65.32 (29.22)	34.32 (25.83)
service & sales	105.57 (20.83)	17.71 (7.92)	17.97 (13.53)
technicians	80.56 (15.89)	29.51 (13.20)	26.70 (20.09)
Permanent work contract (n, %)	464.39 (91.61)	207.44 (92.79)	130.69 (98.34)
Works in shifts (n, %)	71.45 (14.09)	12.77 (5.71)	0.00 (0.00)
Driver license (n, %)	461.48 (91.03)	209.44 (93.69)	127.67 (96.07)
Car access (n, %)	461.48 (91.03)	209.44 (93.69)	127.67 (96.07)
National PT season ticket (n, %)	29.74 (5.87)	23.00 (10.29)	13.19 (9.92)
Half-fare PT ticket (n, %)	177.31 (34.98)	83.42 (37.31)	44.32 (33.35)

Table 7.3: Sample comparison by telework status (weighted).

The primary goal of sequence analysis is then to extract simplified information from the state sequence. We use Shannon's entropy as a measure of the diversity of states. Letting p_i denote the proportion of cases in state i at the considered position, the transversal entropy is defined as (Gabadinho *et al.*, 2011)

$$h(p_1, \dots, p_a) = -\sum_{i=1}^{a} p_i \log(p_i) \tag{7.1}$$

where a is the size of the alphabet, i.e., the number of unique states. The entropy is 0 when all cases are in the same state and maximal when we have a uniform distribution over the states.

Similarly, the longitudinal Shannon entropy (for each sequence individually) is (Gabadinho *et al.*, 2011)

$$h(\pi_1, \dots, \pi_a) = -\sum_{i=1}^{a} \pi_i \log(\pi_i) \tag{7.2}$$

where π_i is the proportion of occurrences of the ith state in the sequence.

As proposed by Song *et al.* (2021) a cluster analyisis of the activity-trip sequences or investigating sequence differences by telework status could be interesting. However, due to the high combinatorial nature of a full day of activity episodes, we found that the within cluster similarities were very low and thus it is difficult to find general patterns. Also, (as in any cluster analysis) dissimilarity measures should be carefully evaluated and compared. As this was not the main emphasize of our paper, clustering was not further pursued as part of the analysis (for an example of activity sequence analysis in the telework context see Su *et al.* 2021).

We use the **TraMineR** R-package (Gabadinho *et al.*, 2011) to analyse the state sequences, i.e., for the index plots (Figure 7.2), entropy and population share computations (Figure 7.3).

7.4.2 *Ordered probit switching regression*

A description of the OPSR modeling framework can be found in Section 6.2 and is not repeated here.

7.4.2.1 *A word on the sensitivity with respect to "rho"*

It immediately follows that the derivative of Equation 6.7 with respect to ρ_j is the IMR scaled by the standard deviation σ_j. The sensitivity of the conditional expectation with respect to ρ_j depends on the IMR. Further, Equation ?? consists of two parts: $\boldsymbol{X_j \beta_j}$ and $\rho_j \sigma_j$IMR (the Heckman correction). In how far the conditional expectation is influenced by "rho" therefore depends on the relative size of the two parts. If $\boldsymbol{X_j \beta_j}$ is relatively small compared to σ_jIMR, then ρ_j plays a relatively more important role for the conditional expectation and thus the treatment effects (depending on the influence on the counterfactual conditional expectation). Furthermore, not accounting for error correlation (dropping the Heckman correction) could lead to very different beta estimates and thereby treatment effects.

7.5 RESULTS

In what follows, we first investigate daily time-use and mobility patterns (disaggregate view) by telework location (i.e., either home, mixture or office). We also report in how far NTWers, NUTWers and UTWers differ with regard to these daily patterns. Subsequently, the descriptive analysis is repeated for weekly time-use and mobility indicators (aggregate view) by telework status (NTWers, NUTWers and UTWers). As should be clear, this group comparison has by now means a causal interpretation. Finally, the OPSR method is employed to estimate telework treatment effects and the preceding descriptive analysis allows us to interpret them.

7.5.1 *Disaggregate analysis by telework location*

To put the following findings into perspective, the share of TWers working fully remote over the weekdays varies between 14.76% and 17.8% which is slightly lower than found in Heimgartner and Axhausen (2024b). The share is quite stable with Mondays being the most popular day to telework.

7.5.1.1 *Activity sequences*

Figure 7.2 presents full index plots of activity sequences highlighting work and travel states by telework location. The visualization illustrates how work activities for office workers (bottom row) are concentrated during regular business hours, structuring the overall activity sequences and confining travel to typical peak periods in the morning, midday, and afternoon. This structured pattern gradually diminishes from office workers to mixture workers and further dissolves among teleworkers (top row), reflecting the increasing flexibility in work schedules and mobility.

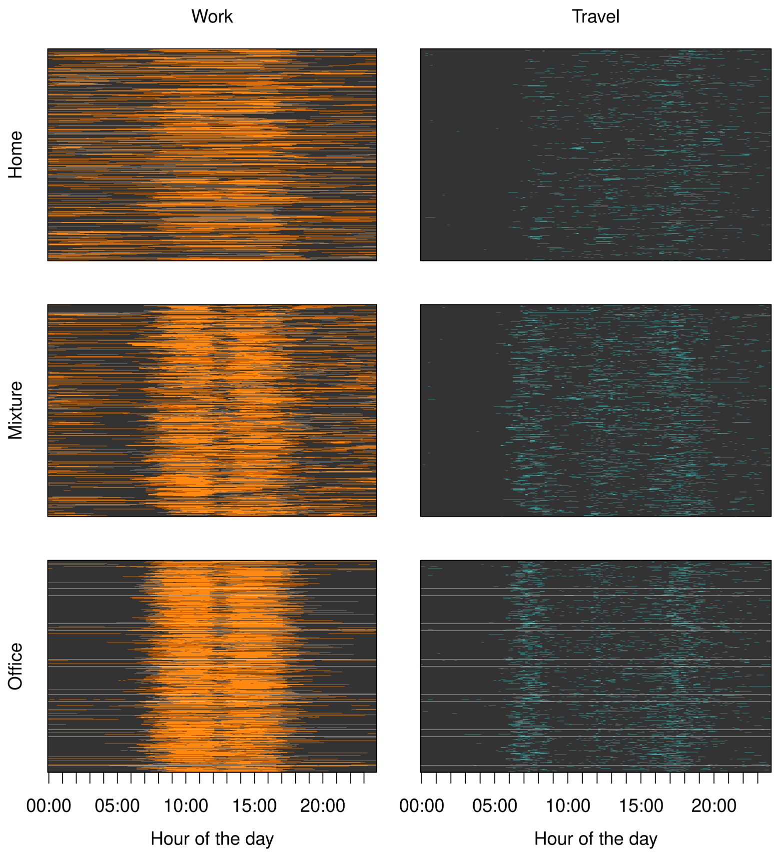

FIGURE 7.2: Activity sequences highlighting work and travel states by telework location.

The "diversity of states" as measured by the longitudinal entropy (Figure 7.3) is slightly lower for TWers. As a reminder, the entropy is 0 when all cases are in the same state and is maximal when the same proportion of cases is observed in each state. On the other hand, the transversal entropy is bounded above by home TWers, while for mixture and office workers pronounced swings between low and high entropy can be observed. Again, this indicates that office work and conventional business hours "align" activity sequences across individuals. Panel 3 highlights that around 20% of TWers prefer to work during unusual hours. Similarly, mixture workers shift some work to late hours or work over-time during off business hours. The last panel emphasizes that the three rush hour peaks still exist and are the most popular hours to travel (in a relative sense). Teleworkers' mobility seems to be depressed throughout the day but especially during the morning rush hours. Mixture workers are particularly mobile during lunch time (potentially commuting during these hours).

7.5.1.2 *Time-use*

Figure 7.4 shows the time spent on the seven distinguished time-use categories by telework location. Median values are further separated by telework status. Further, a notch is drawn in each side of the boxes. If the notches of two plots do not overlap, this is "strong evidence" that the two median values differ (Chambers *et al.*, 1983, p. 62). Hours worked (panel 6) seem to be lower for TWers (especially NUTWers). However, as already alluded, part-time work is more common among NUTWers. Together with the evidence from Table 7.2 that the full-time equivalent hours worked are almost identical across the three groups, we conclude that NUTWers working part-time spread the workload over the available days (even the "non-work" days). The only noticeable other difference is that TWers spend less time traveling. Notably UTWers show a considerable gap (of around one hour) on travel spent when teleworking versus when commuting to the office. As we will see, UTWers tend to have longer commutes and use the train as a commuting mode. The substitution patterns (for the travel time savings) are not that obvious: The distributions for TWers are comparably larger than for mixture and office workers, indicating that substitution patterns could be diverse. The only two categories showing higher median values are leisure and sleeping. We conclude that time allocation is fairly similar across telework location and telework status, with travel being the obvious exception, especially for UTWers.

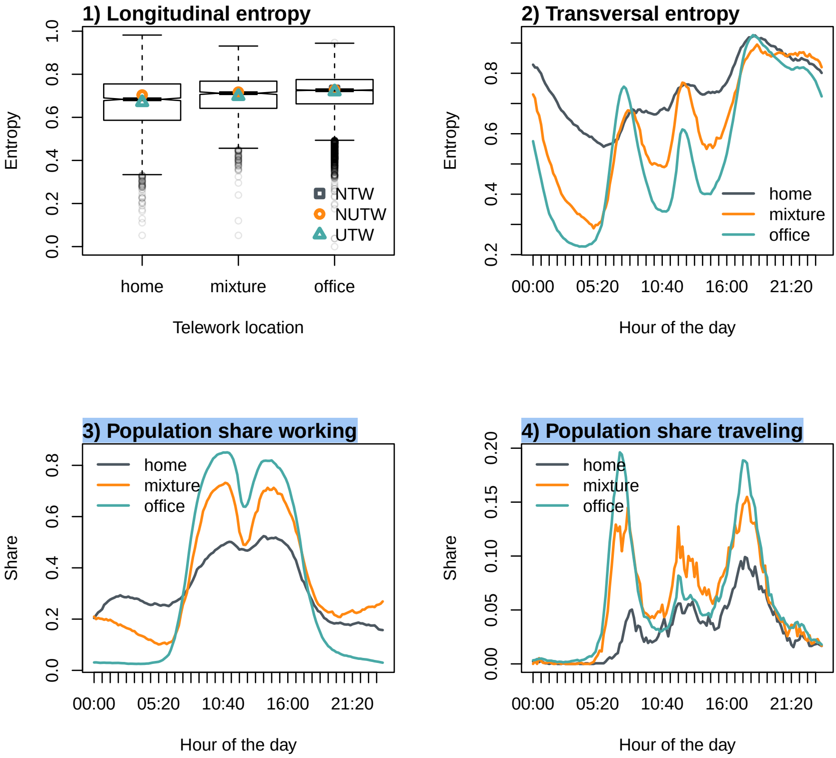

FIGURE 7.3: Longitudinal and transversal etropy, population share working and traveling throughout the day by telework location.

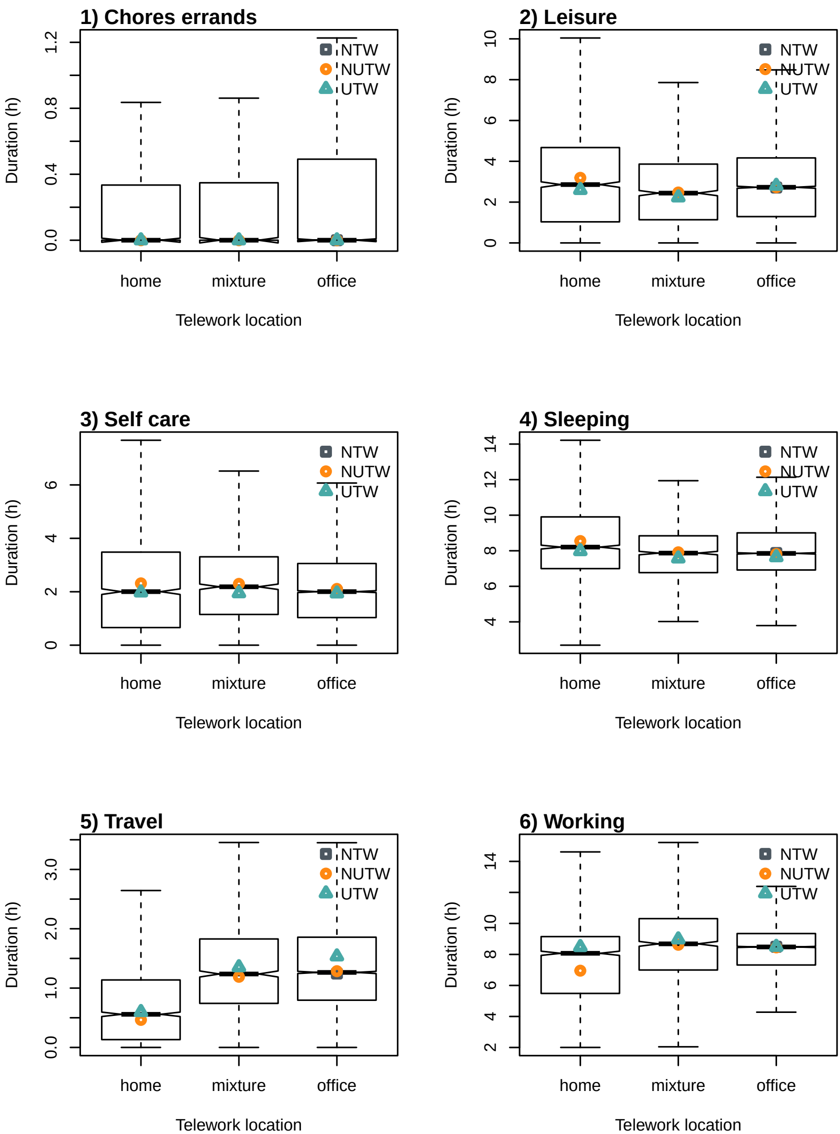

Figure 7.4: Time-use indicators by telework location (disaggregate view). Separate median values by telework status.

7.5.1.3 *Mobility*

Figure 7.5 shows mobility indicators by telework location. Again, median respectively mean values are further distinguished by telework status. Panel 1 indicates that the previous discussion on travel times carries over to traveled distance. Panel 2 shows that telework depresses traveled distance in particular for motorized individual transport (mit) and train. Meanwhile, TWers (in particular UTWers) tend to be train commuters on regular office workdays. Fully remote TWers make fewer trips across all modes and the full trip count distribution is shifted to the left roughly by two trips. We investigated this shift further and found that it is purely driven by main commuting modes (mit and train) with two fewer trips by train and two to six fewer trips by car (trip distributions by modes are not shown here). Similarly, bike also shows this decrease of two trips, indicating its use as a commuting mode while little compensating leisure travel by TWers exists. Similarly mode shares for TWers are substantially smaller for mit and train, while walk almost makes up 40%. The last panel shows the number of generated trips by hour of the day and normalized for number of tracking study participants by telework location. The evening rush hour is the busiest hour and telework only marginally contributes to flattening that peak. Contrary, the morning and midday peak hours generate fewer trips for TWers. Here, one has to keep in mind, that between 14.76% and 14.76% of the workforce teleworks on any given day. Additionally, teleworkers tend to live in an urban environment. Therefore the flattening of the peak hours on main commuting axes might not be noticeable.

7.5.2 *Aggregate analysis by telework status*

7.5.2.1 *Time-use*

Figure 7.6 shows that in a typical full-time equivalent workweek, time-allocation seems to be fairly similar across the teleworker groups. As already observed in Table 7.3 UTWers are less frequent grocery shoppers which could explain the less time spent on chores and errands which are likely integrated into commuting trips of less frequent TWers. The somewhat higher leisure and self-care time consumption of NUTWers can potentially be attributed to more prevalent part-time work and is less prevalent among UTWers. Meanwhile there seems to be a linear increasing trend in sleep and decreasing trend in travel indicating that part of the foregone commutes is simply substituted with more sleep. The difference in total hours worked

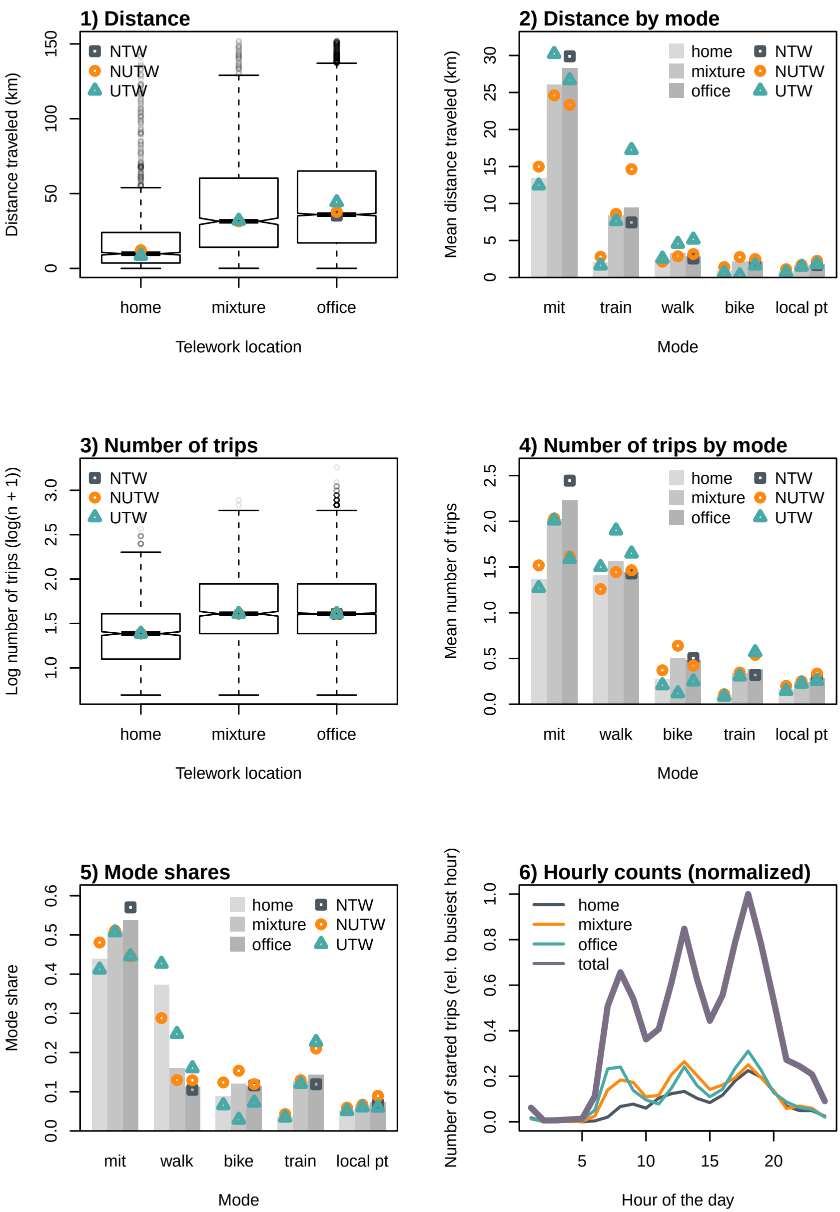

FIGURE 7.5: Mobility indicators by telework location (disaggregate view). Separate median (for the boxplots) or mean values (for the barplots) by telework status.

was already discussed in Table 7.2 and is together with the observations at the disaggregate level a manifest of the higher workload (rather than work-ethics).

7.5.2.2 *Mobility*

Figure 7.7 indicates that UTWers travel less distance and make fewer trips across all modes except for walk but in particular for mit. Despite UTWers being particularly inclined to use the train on regular office workdays, the foregone train travel on home office days is not fully compensated. However, mode (distance) shares are not that different across the groups with TWers having slightly higher train shares and lower mit shares compared to non-TWers. Meanwhile UTWers prefer walk to bike. Panel 6 shows that UTWers have slightly further commutes which explains the longer distances traveled on regular office days. However, the direction of potential causality is not clear here: In spirit of Ravalet and Rérat (2019) and de Vos *et al.* (2018) it could be argued that TWers indeed accept longer commutes (and relocated) while longer commutes could simply incentivize more telework in the first place. In general, the insights seem to be consistent with the disaggregate analysis and patterns observed on home office days (more strongly) translate to patterns observed for UTWers.

7.5.2.3 *Intermediate summary*

In summary, telework seems to influence time scheduling rather than time allocation since the usual structure regular business hours provide is less respected when teleworking. This leads to less aligned activity patterns and thus higher transversal entropy throughout the day of TWers. TWers make significantly fewer trips and cover significantly less distance. The most affected modes are the main commuting modes, e.g., mpt and train. However, TWers tend to have PT subscriptions and use PT when commuting, leading to overall very similar mode shares over a full workweek. The descriptive analysis portrays a picture of reduced transport demand – more flexible time scheduling and foregone commutes being the main implications of telework. TWers tend to have longer commutes and therefore potentially have a stronger incentive to telework while at the same time have a higher potential to decrease distance traveled. Meanwhile mixture workers have very similar activity and mobility patterns to regular office workers with a somewhat flattened morning peak hour (as the commute is delayed to later hours, most likely the midday peak).

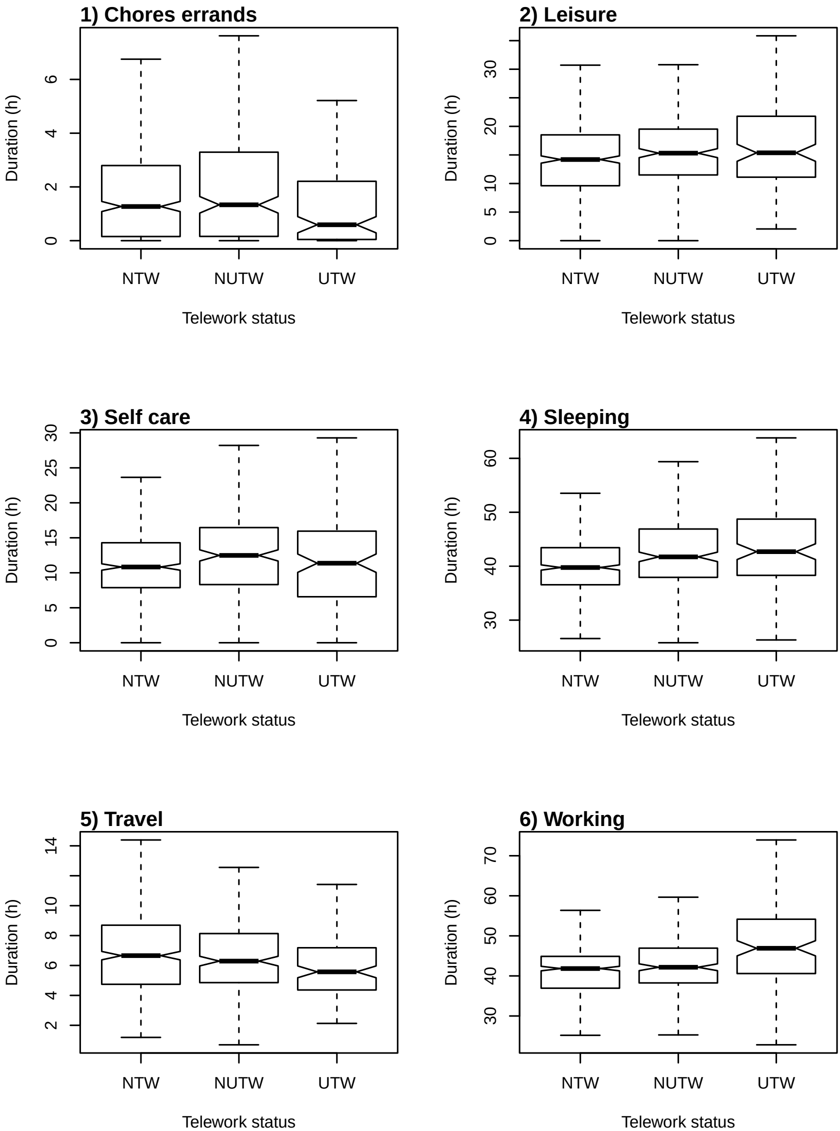

Figure 7.6: Weekly time-use indicators by telework status (aggregate view).

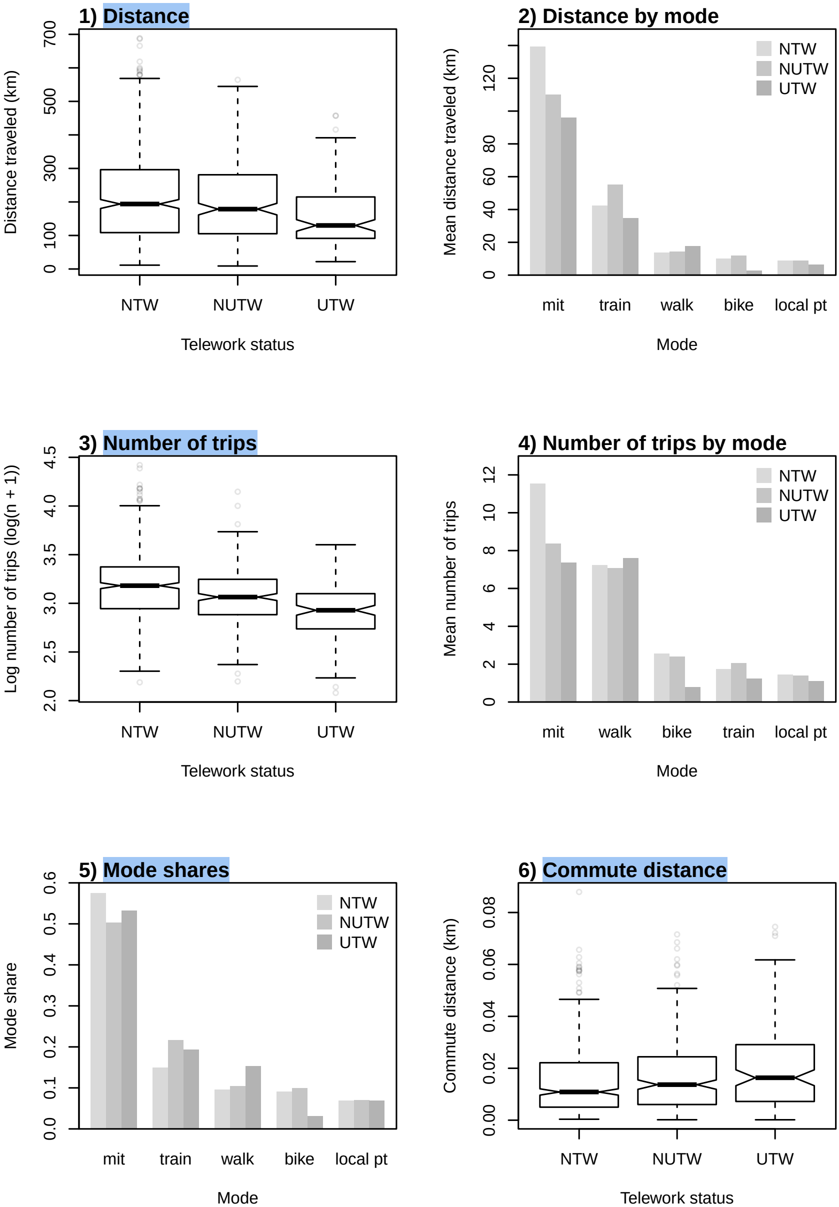

FIGURE 7.7: Weekly mobility indicators by telework status (aggregate view).

7.5.3 *Telework treatment effects*

This section presents the results based on the OPSR methodology with an emphasize on treatment effects rather than individual model parameters and their behavioral implications. We first estimated the full specified model and then 9 further models, dropping insignificant coefficients at the 90% level down to the 10% level. The model with the lowest AIC was then further reduced for the outcome process of the UTWers in order to avoid overfitting. Since the data is rather sparse (especially for the UTWers) the bias-variance trade-off was carefully evaluated, using k-fold cross-validation (with $k = 10$) and out-of-sample log-likelihood as our loss. We find that the likelihood ratio test would always favor the full model, while cross-validation selects sparser models. The computation of treatment effects is based on "counterfactual" predictions and therefore hinges upon the prediction accuracy.

The final model is compared to other benchmark models (the null, full and AIC-preferred model) in Table A.1 along with conventional goodness of fit indicators. The likelihood-based pseudo R^2 indicates mediocre fit for the selection process (pseudo-R^2 equally-likely = -965.68; pseudo-R^2 market-share = -848.62), while R^2 values for the continuous outcomes indicate good fit for NTWers (R^2 = 0.64) and NUTWers (R^2 = 0.66) and mediocre fit for UTWers (R^2 = 0.32). This can partly be attributed to the importance of the commuting distance which was included as an explanatory variable (and naturally plays an important role for the first two groups while less so for the UTWers). Parameter estimates are stable when excluding insignificant terms (i.e., they are similar in magnitude and have the same signs).

Table 7.4 presents the estimates of the final model. In particular, there is significant error correlation (for "Rho 2") and the Wald χ^2 test (with the null being all Rho coefficients are zero) is clearly rejected. Further, distinct processes seem to govern the final outcome (log weekly km) with different variables remaining in the final process specifications. This hints that accounting for error correlation (and estimating the full covariance matrix) is necessary while also treating the TWer groups as distinct segments with their separately estimated parameters. However, if variables enter more than one continuous process specification (e.g., household size) and at least one of the parameters is found significant, then the direction of effect is shared across the three groups (hinting that the processes follow at least some common pattern).

The selection process (ordered probit model for the telework frequency) is a labor market outcome and governed by both employers' and employees' preferences as well as feasibility constraints. Telework allowance and teleworkability (as measured by the TW frequency during COVID-related lockdowns) significantly influence TW adoption with socio-demographic attributes only providing limited information (at least the ones available in our data).

The key value proposition of using a model (at least in this paper) is to investigate counterfactual outcomes (i.e., outcomes that are never observed in real life but could manifest if conditions change). Figure 7.8 presents all potential counterfactual outcomes of telework adoption and differentiates among the three TW groups. The diagonal depicts distributions of weekly kilometers driven in any given TW scenario and separate by the current (factual) TW status. The weighted median values are shown as red numbers. I.e., the first panel shows the weekly kilometers driven in a world without telework (non-teleworking, NTWing). Such a scenario is factual for the current NTWers but counterfactual for the other two groups. The distributions indicate that current NTWers travel less than current NUTWers than UTWers. The lower triangular panels compare the model-implied (predicted) weekly kilometers traveled of two scenarios and again separate by TW status. The red line indicates the 45-degree line of equal travel while the red squares depict the weighted median values (corresponding to the ones reported in the diagonal panels). The upper triangular panels show weighted average treatment effects (ATE). For example, the lowest leftmost panel compares NTWing (x-axis) to UTWing (y-axis). Almost all points lie below the red line indicating that almost all individuals would reduce distance traveled when switching from NTWing to NUTWing. Overall, this reduction accounts to 115 km foregone travel per individual and week when switching from NTWing to UTWing (most upper and rightmost panel reporting the ATE).

In all scenarios the current UTWers always travel more than current NUTWers that travel more than current NTWers. ATE are always negative with very similar treatment effects (TE) when switching from NTWing to NUTWing and NUTWing to UTWing. Only few individuals would increase weekly kilometers traveled (when TWing more) under any given scenario combination.

The ATE are presented along group-specific treatment effects in Table 7.5. Beyond the previous insights, treatment effects indicate that NTWers reduce travel in particular when switching from NTWing to NUTWing, while

	Selection	NTW (492)	NUTW (259)	UTW (128)
Intercept		2.89 (0.31)***	3.27 (0.27)***	2.71 (0.47)***
Telework allowed	0.82 (0.16)***			
Teleworkability	0.25 (0.04)***			
Start month (ref: Jan.)				
July		0.38 (0.24)		
August		0.19 (0.23)		
September		0.27 (0.23)		
October		0.29 (0.23)		
November		0.40 (0.24)		
December		0.25 (0.23)		
Log commute km	0.12 (0.08)	0.58 (0.04)***	0.69 (0.04)***	0.48 (0.06)***
Age	0.01 (0.01)*			
Has dogs	0.63 (0.19)***	0.18 (0.07)*	0.14 (0.07)	
Driver license	0.25 (0.27)	0.20 (0.09)*		
Higher education				0.21 (0.10)*
Fixed workplace	−0.40 (0.20)*	−0.15 (0.09)	−0.28 (0.10)**	
Grocery shopper		0.08 (0.06)	−0.12 (0.07)	
HH income (ref: <4000 CHF)				
4001 - 8000 CHF	−0.63 (0.33)			
8001 - 12000 CHF	−0.81 (0.32)*			
12001 - 16000 CHF	−0.87 (0.33)**			
16000+ CHF	−0.23 (0.35)			
HH size	0.23 (0.09)**		0.07 (0.03)*	0.16 (0.04)***
ISCO				
Clerical	0.20 (0.13)			
Managers	−0.27 (0.15)			
Agri, forest and fishery	0.16 (0.37)			
Married			−0.11 (0.07)	−0.34 (0.12)**
Number of children	−0.14 (0.11)	−0.08 (0.03)**		
Frequent online shopper	0.09 (0.13)			0.39 (0.23)
Parking home	0.50 (0.39)			
Parking work	−0.17 (0.14)	0.14 (0.05)**	−0.08 (0.06)	
Permanent work contract	0.34 (0.27)	0.29 (0.10)**		
Res. loc. (ref: Rural)				
Suburban				−0.53 (0.20)**
Urban				−0.56 (0.20)**
Male	−0.25 (0.14)	0.17 (0.06)**	0.10 (0.07)	
Works in shifts		−0.09 (0.07)	−0.25 (0.11)*	
Swiss	−0.33 (0.17)			
Vacation during study		−0.07 (0.07)	0.12 (0.07)	
Workload		0.02 (0.01)	0.01 (0.02)	0.06 (0.03)*
Has kids below 12			−0.19 (0.08)*	
Kappa 1	2.39 (0.76)**			
Kappa 2	3.60 (0.75)***			
Sigma 1	0.39 (0.02)***			
Sigma 2	0.41 (0.04)***			
Sigma 3	0.46 (0.06)***			
Rho 1	0.19 (0.42)			
Rho 2	0.50 (0.10)***			
Rho 3	0.20 (0.40)			
AIC	2172.10			
BIC	2511.40			
Log Likelihood	−1015.05			
Pseudo R^2 (EL)	0.31			
Pseudo R^2 (MS)	0.21			
R^2 (total)	0.61			
R^2 (1)	0.64			
R^2 (2)	0.66			
R^2 (3)	0.32			
Num. obs.	879			

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

TABLE 7.4: Model estimates.

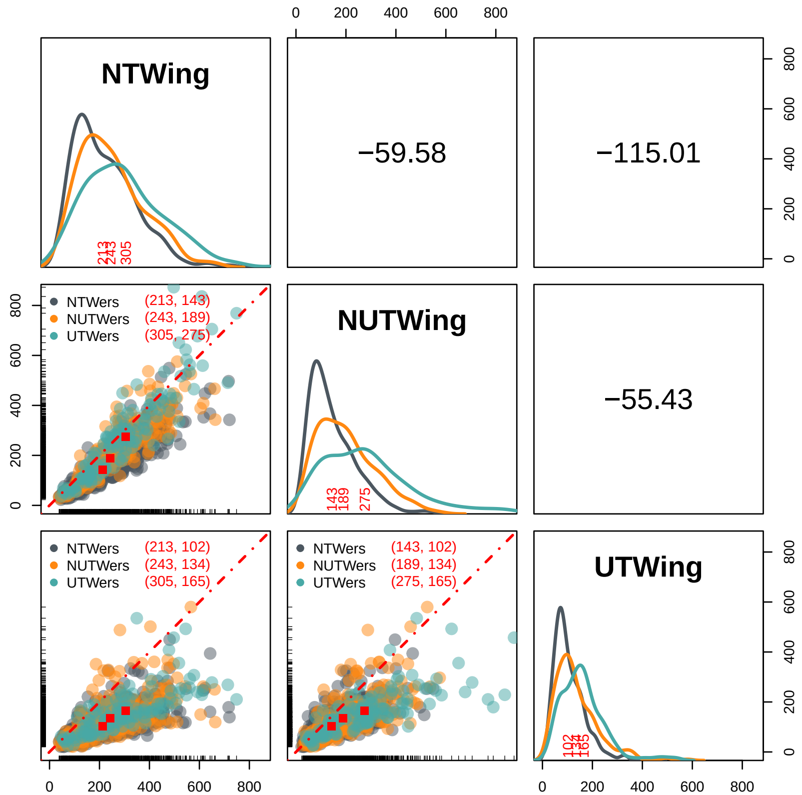

Figure 7.8: Pairs plot: Comparison of conditional expectations (weekly km traveled) by telework status in the lower panel. Corresponding distributions on the diagonal. Average treatment effects in the upper panel.

UTWers show a stronger treatment effect when switching from NUTWing to UTWing (compared to NTWing to NUTWing). Meanwhile, NUTWers show very similar treatment effects in the two scenarios. All TE and ATE are significant at the 0.1% level as confirmed by a pairwise weighted t test.

The upper half of Table 7.5 also implies that treatment effects are much stronger than what simple group comparison would suggest: The counterfactual weekly kilometers traveled by UTWers under the NTWing scenario (305 km) are substantially larger than the factual weekly kilometers traveled by the current NTWers (213 km). In that sense it is right to state that telework reduces the mobility of a particularly mobile group (as speculated in Heimgartner and Axhausen 2023c).

	Telework status			
	NTWers	NUTWers	UTWers	ATE
Observed mean weekly km	208.637	185.261	160.142	
Estimated mean weekly km				
NTWing	212.87	243.234	304.667	
NUTWing	142.959	189.228	275.145	
UTWing	101.889	133.895	164.755	
Treatment effects				
NTWing→NUTWing	-69.911^{***}	-54.006^{***}	-29.523^{***}	-59.576^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
NTWing→UTWing	-110.981^{***}	-109.338^{***}	-139.912^{***}	-115.009^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
NUTWing→UTWing	-41.07^{***}	-55.332^{***}	-110.39^{***}	-55.433^{***}
	(0.000)	(0.000)	(0.000)	(0.000)

[1] Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1;

[2] p values of paired weighted t test in brackets

Table 7.5: Estimated factual and counterfactual mean weekly kilometers traveled and treatment effects.

Unit treatment effects (UTE) are computed by dividing the TE from Table 7.5 by the difference in telework frequency. They are reported in Table 7.6 along the average two-way commute distance by TW status, which allows us to comment on compensating travel beyond foregone commute. In the disaggregate view of the descriptive analysis we compared teleworking days to office and mixture days while in the aggregate view we investigated group differences. But of course, there was an inherent connection between the two, namely that UTWers have (by definition) more such individual home office days than NUTWers than NTWers. Unit treatment effects allow us to standardize group differences by rescaling the effect to a marginal treatment (per home office day).

For all three groups, UTE almost exactly correspond to the foregone two-way commute when going from NTWing to UTWing. The aforementioned non-linearities in the strength of treatment effects translates to UTE: In other words, for NTWers and NUTWers some compensating travel (beyond foregone commutes) exist in the second half of TW adoption (NUTWing to UTWing), while for UTWers some compensating travel exists on the first half (NTWing to NUTWing). We speculate that UTWers living in a more urban environment initially don't adjust non-work related travel patterns but only do so, once the new center of trip generatation becomes their home more permanently.

	Telework status		
	NTWers	NUTWers	UTWers
WFH (d/week)	0.000	1.242	3.563
2-way commute (km)	27.517	30.969	37.969
NTWing→NUTWing	-56.307	-43.497	-23.778
NTWing→UTWing	-31.145	-30.684	-39.264
NUTWing→UTWing	-17.689	-23.832	-47.545

TABLE 7.6: Unit treatment effects kilometers traveled.

Finally, we can estimate forgone travel activity by predicting weekly kilometers traveled in a world without telework and then compare the numbers to the status quo. The weighted travel reduction accounts to -16% relative to the no telework reference. This number is very similar to the findings by Heimgartner *et al.* (2024b) and Sallard (2024) for the Zurich population using a simulation approach. They also find that mode shares are relatively stable across the telework and non-telework population which we confirmed in the descriptive analysis.

Our findings also align with Wang and Mokhtarian (2024) who report that treatment effects are always negative (with the exception of the current UTWers switching from NTWing to NUTWing, which we don't confirm), travel reduction corresponds roughly to the foregone commute and the asymmetry between adjustments of the NTWers (who more strongly reduce travel when adopting some telework) and UTWers (who do so more pronounced when switching from NUTWing to UTWing).

7.5.3.1 *Not accounting for selection on unobservables*

As already alluded, we find significant error correlation implying that selection on unobservables exists which leads to selection bias if not accounted for. As we will illustrate now, this also compromises treatment effects. We derive a new model (labeled "Rho = 0" below) from the one discussed above (labeled "OPSR" below) by setting the "Rho" coefficients to 0. I.e., this is the same as separately estimating an ordered probit model and three linear regression models (while using our final model specification).

The implications for treatment effects and average treatment effects are presented in Table 7.7: While not accounting for selection on unobservables still predicts negative TE and ATE, they are generally underestimated quite substantially.

7.6 SUMMARY AND DISCUSSION

Overall, our findings strengthen the narrative that telework reduces traveled distance and that small rebound effects can not offset foregone commutes by a wide margin. We estimate, that the weighted travel reduction accounts to -16% comparing the current telework situation to the no telework reference. We find that unit treatment effects roughly correspond to the two-way commute distance. NTWers and NUTWers show stronger effects when adopting some telework from initially NTWing compared to switching from NUTWing to UTWing, while UTWers show exactly the inverse pattern. Our estimated treatment effects suggest that travel reduction is much larger than simple group comparison would suggest. This is because the counterfactual weekly kilometers traveled by TWers in a no telework scenario are substantially larger than the factual weekly kilometers traveled by the current NTWers (selection on observables). Beyond that, we show that not accounting for error correlation (selection on unobservables) potentially underestimates the true treatment effects quite substantially (while still confirming that telework reduces overall travel activity). Our results are in line with studies either employing the same method or using a similar study context. They are intuitive yet less appealing than the story of second order effects completely offsetting any foregone commute. The descriptive

	Treatment	Telework status			ATE
		NTWers	NUTWers	UTWers	
OPSR	NTWing→NUTWing	-69.91	-54.01	-29.52	-59.58
	NTWing→UTWing	-110.98	-109.34	-139.91	-115.01
	NUTWing→UTWing	-41.07	-55.33	-110.39	-55.43
Rho = 0	NTWing→NUTWing	-38.24	-40.88	-47.31	-40.32
	NTWing→UTWing	-94.32	-85.61	-107.31	-94.06
	NUTWing→UTWing	-56.07	-44.73	-60.00	-53.74
Δ	NTWing→NUTWing	-31.67	-13.12	17.79	-19.25
	NTWing→UTWing	-16.66	-23.73	-32.60	-20.95
	NUTWing→UTWing	15.00	-10.61	-50.39	-1.69
%	NTWing→NUTWing	-45.30	-24.30	60.25	-32.32
	NTWing→UTWing	-15.01	-21.70	-23.30	-18.21
	NUTWing→UTWing	36.53	-19.17	-45.65	-3.05

TABLE 7.7: Implications for treatment effects if selection on unobservables is not accounted for.

analysis portrays a similar picture with depressed transport demand – more flexible time scheduling and travel time savings being the main implications of telework while overall time allocation is very similar between the three distinguished groups. We know that all models are wrong, but hope that our modeling results are less wrong thanks to accounting for self-selection when estimating telework treatment effects.

8

ESTIMATION AND POST-ESTIMATION ROUTINES FOR OPSR

In dubio pro reo.

The **OPSR** R-package allows analysts to estimate ordered probit switching regression models, a form of endogenous switching regression, accounting for error correlation between an ordinal selection and continuous outcome processes (e.g., the well-known Tobit-5 model for the case of two regimes). **OPSRtools**, introduced in this paper, helps the analyst during model selection (`opsr_select()`), to cross-validate (`opsr_kfold()` and `kfplot()`), to compute treatment effects (`opsr_ate()`) and to visualize the key insights from a model (`pairs()`). `print()` methods for the various underlying objects allow the analyst to easily grasp the object's key information. The reference manual can be found in Appendix A.3.2.

This chapter is based on the following paper

Heimgartner D. (2025) **OPSRtools**: Estimation and Post-Estimation Routines for the **OPSR** Package, unpublished work.

8.1 INTRODUCTION

The **OPSR** R-package, introduced in Heimgartner and Wang (2025a), provides an easy-to-use, fast and memory efficient interface to ordered probit switching regression (OPSR). OPSR is a form of endogenous switching regression, accounting for error correlation between an ordinal selection and continuous outcome processes. In spirit of Heckman (1979), self-selection bias might result, if this error correlation is not explicitly modeled.

While the **OPSR** package contains the minimal machinery to estimate such models, present their results and compute conditional expectations, it does not provide routines supporting model selection, cross-validation and the computation of treatment and average treatment effects. This is where **OPSRtools** steps in. Along functions and methods to compute and present (`print()`) the statistics in appropriate form, it also contains visualization routines.

The remainder of this paper is organized as follows. In Section 8.2 the key functionality of the package is illustrated. Section 8.3 investigates differences in telework treatment effects if the error correlation is not accounted for as well as raises concerns about potential identification issues. Section 8.4 concludes.

8.2 ILLUSTRATIONS

Let us revisit the full model from Chapter 7, modeling telework adoption and weekly kilometers traveled. Telework adoption was differentiated into three ordered segments: no telework (NTW), non-usual telework (NUTW, <3 days/week) and usual telework (UTW, 3+ days/week). The data, based on the TimeUse+ study (Winkler *et al.*, 2024), is attached, documented (`?timeuse`) and can be loaded by

```
R> data("timeuse", package = "OPSRtools")
```

Using **OPSR**'s functionality, the model can be estimated by (the formula `f` is hidden here for brevity but can be found on Page 146 under *Initial model*)

```
R> fit <- opsr(f, data = timeuse, weights = timeuse$weight)
```

This model is likely to be over-specified and as a usual first step, the analyst starts by excluding insignificant variables (above some p value threshold). Given the above formula object with many terms/variables, this process can be tedious or even error prone – boring at best. The function `opsr_step()` allows the modeler to do this automatically. For example, excluding all variables which are not significant at the 10% level

```
R> fit_10 <- opsr_step(fit, pval = 0.1, printLevel = 0)
R> summary(fit_10)

Call:
opsr(formula = wfh | log_weekly_km ~ wfh_allowed + teleworkability +
    dogs + fixed_workplace + hh_size + swiss | log_commute_km +
    driverlicense + n_children + parking_work + permanent_employed +
    sex_male + workload | log_commute_km + fixed_workplace +
    grocery_shopper + sex_male + shift_work + vacation | log_commute_km +
    driverlicense + hh_size + married + res_loc, data = timeuse,
    weights = timeuse$weight, printLevel = 0)

BFGS maximization, 191 iterations
Return code 0: successful convergence
```

```
Runtime: 0.675 secs
Number of regimes: 3
Number of observations: 879 (492, 259, 128)
Estimated parameters: 36

Log-Likelihood: -1086
AIC: 2243
BIC: 2415
Pseudo R-squared (EL): 0.308
Pseudo R-squared (MS): 0.213
Multiple R-squared: 0.608 (0.626, 0.655, 0.352)

Estimates:
                      Estimate Std. error t value Pr(> t)
kappa1                  1.3050     0.3531    3.70 0.00022 ***
kappa2                  2.4208     0.3624    6.68 2.4e-11 ***
s_wfh_allowed           0.7730     0.1439    5.37 7.8e-08 ***
s_teleworkability       0.2427     0.0333    7.30 3.0e-13 ***
s_dogs                  0.5144     0.1780    2.89 0.00386 **
s_fixed_workplace      -0.3075     0.2240   -1.37 0.16976
s_hh_size               0.1270     0.0529    2.40 0.01632 *
s_swiss                -0.1278     0.1624   -0.79 0.43146
o1_(Intercept)          3.0890     0.1946   15.87 < 2e-16 ***
o1_log_commute_km       0.5669     0.0377   15.04 < 2e-16 ***
o1_driverlicense        0.2239     0.1017    2.20 0.02777 *
o1_n_children          -0.0493     0.0236   -2.09 0.03688 *
o1_parking_work         0.1577     0.0567    2.78 0.00539 **
o1_permanent_employed   0.2550     0.0927    2.75 0.00594 **
o1_sex_male             0.1464     0.0519    2.82 0.00479 **
o1_workload             0.0188     0.0135    1.39 0.16373
o2_(Intercept)          3.3560     0.2009   16.70 < 2e-16 ***
o2_log_commute_km       0.6898     0.0452   15.27 < 2e-16 ***
o2_fixed_workplace     -0.1801     0.1163   -1.55 0.12145
o2_grocery_shopper     -0.1026     0.0716   -1.43 0.15168
o2_sex_male             0.1199     0.0744    1.61 0.10710
o2_shift_work          -0.0878     0.0920   -0.95 0.33981
o2_vacation             0.1013     0.0736    1.38 0.16842
o3_(Intercept)          4.1965     0.4302    9.75 < 2e-16 ***
o3_log_commute_km       0.4844     0.0572    8.48 < 2e-16 ***
o3_driverlicense        0.2234     0.2317    0.96 0.33491
o3_hh_size              0.1071     0.0432    2.48 0.01309 *
o3_married             -0.3046     0.1423   -2.14 0.03229 *
o3_res_locsuburban     -0.5626     0.2045   -2.75 0.00594 **
```

```
o3_res_locurban        -0.5971     0.2102   -2.84 0.00450 **
sigma1                  0.4057     0.0203   19.96 < 2e-16 ***
sigma2                  0.4152     0.0409   10.15 < 2e-16 ***
sigma3                  0.5729     0.1065    5.38 7.4e-08 ***
rho1                    0.0880     0.2515    0.35 0.72650
rho2                    0.4233     0.1186    3.57 0.00036 ***
rho3                   -0.6776     0.2046   -3.31 0.00092 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Wald chi2 (null): 1004 on 25 DF, p-value: < 0
Wald chi2 (rho): 22.7 on 3 DF, p-value: < 0
```

where `printLevel = 0` is passed to `opsr()` and avoids printing working information during maximum likelihood estimation. `opsr_step()` is aware of factor variables and keeps the factor if one corresponding coefficient is below the selected `pval`.

While this model (`fit_10`) has considerably fewer parameters than `fit`, it is not necessarily the "best" model. To more rigorously sparsify the model and carefully evaluate each intermediate model, the function `opsr_select()` can be used

```
R> fit_aic <- opsr_select(fit, loss = "aic", printLevel = 0)
```

where `"aic"` specifies that model selection is based on AIC. Other available options are `"bic"` for BIC and `"lrt"` for a likelihood ratio test. The above call yields an object of class '`opsr.select`' which can be printed to provide more information about the selection process (and elimination history, which is omitted here for brevity)

```
R> print(fit_aic, print.elim.hist = FALSE)

Stepwise Model Path

Call:
opsr_select(object = fit, loss = "aic", printLevel = 0)

Initial model:
wfh | log_weekly_km ~ wfh_allowed + teleworkability + start_tracking +
    log_commute_km + age + dogs + driverlicense + educ_higher +
    fixed_workplace + grocery_shopper + hh_income + hh_size +
    isco_clerical + isco_craft + isco_managers + isco_plant +
    isco_professionals + isco_service + isco_agri + isco_tech +
    married + n_children + freq_onl_order + parking_home + parking_work +
```

```
    permanent_employed + rents_home + res_loc + sex_male + shift_work +
    swiss + vacation + workload + young_kids | start_tracking +
    log_commute_km + age + dogs + driverlicense + educ_higher +
    fixed_workplace + grocery_shopper + hh_income + hh_size +
    married + n_children + freq_onl_order + parking_home + parking_work +
    permanent_employed + rents_home + res_loc + sex_male + shift_work +
    swiss + vacation + workload + young_kids | start_tracking +
    log_commute_km + age + dogs + driverlicense + educ_higher +
    fixed_workplace + grocery_shopper + hh_income + hh_size +
    married + n_children + freq_onl_order + parking_home + parking_work +
    permanent_employed + rents_home + res_loc + sex_male + shift_work +
    swiss + vacation + workload + young_kids | start_tracking +
    log_commute_km + age + dogs + driverlicense + educ_higher +
    fixed_workplace + grocery_shopper + hh_income + hh_size +
    married + n_children + freq_onl_order + parking_work + permanent_employed +
    rents_home + res_loc + sex_male + swiss + vacation + workload +
    young_kids

Final model:
wfh | log_weekly_km ~ wfh_allowed + teleworkability + log_commute_km +
    age + dogs + driverlicense + fixed_workplace + hh_income +
    hh_size + isco_clerical + isco_managers + isco_agri + n_children +
    freq_onl_order + parking_home + parking_work + permanent_employed +
    sex_male + swiss | start_tracking + log_commute_km + dogs +
    driverlicense + fixed_workplace + grocery_shopper + n_children +
    parking_work + permanent_employed + sex_male + shift_work +
    vacation + workload | log_commute_km + dogs + fixed_workplace +
    grocery_shopper + hh_size + married + parking_work + sex_male +
    shift_work + vacation + workload + young_kids | log_commute_km +
    driverlicense + educ_higher + hh_size + married + freq_onl_order +
    parking_work + res_loc + swiss + workload

Runtime: 1.45 mins

Model comparison:
  Current winner Current Opponent   Test Winner
1  initial model    2208     2202   5.19      2
2         step.1    2202     2197   5.80      2
3         step.2    2197     2195   2.07      2
4         step.3    2195     2181  13.40      2
5         step.4    2181     2168  12.69      2
6         step.5    2168     2159   9.10      2
7         step.6    2159     2178 -18.22      1
```

```
8         step.6    2159     2207 -47.69      1
9         step.6    2159     2243 -83.78      1
```

The final model (after the sixth iteration) has improved AIC by 49 points and would be preferred over `fit_10`. The model comparison table reads as follows

- Current winner: The currently best performing model.
- Current: "Loss" value (here AIC) of the current winner.
- Opponent: "Loss" value of the model at the current step.
- Test: Test-statistic (here AIC difference).
- Winner: Selected model based on the test-statistic (current winner in the next step).

The three models can be compared by

```
R> print(anova(fit_10, fit_aic, fit), print.formula = FALSE)

Likelihood Ratio Test

  logLik    Df  Test Restrictions Pr(>Chi)
1  -1086    36
2  -1006    74   160           38   <2e-16 ***
3   -953   151   106           77    0.017 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

where the likelihood ratio test would select the full model. However, the full model is potentially over-fitting the data (in particular for the usual teleworkers, UTWers). To further investigate the out-of-sample (OOS) performance, k-fold cross-validation can be performed

```
R> kfold <- opsr_kfold(fit, k = 10, verbose = FALSE, printLevel = 0)
R> kfold_10 <- opsr_kfold(fit_10, k = 10, verbose = FALSE, printLevel = 0)
R> kfold_aic <- opsr_kfold(fit_aic, k = 10, verbose = FALSE, printLevel = 0)
```

The resulting object of class '`opsr.kfold`' is a nested list: It contains for each fold different out-of-sample loss computations

- `z`: The regime/treatment membership (here telework status) of the test data.

- `ll`: The OOS log-likelihood.
- `ll_mean`: `ll` averaged over each regime and in total.
- `ll_p`: The OOS log-likelihood for the selection process (ordered probit model).
- `ll_p_mean`: `ll_p` averaged over each regime and in total.
- `r2`: The OOS coefficient of determination (R^2) for each regime and in total.

OPSRtools provides an extract method to collect the desired information

```
R> ll_mean <- kfold["ll_mean"]
R> list2df(ll_mean)

    Total     o1    o2    o3
1  -1.133 -0.722 -1.42 -2.26
2  -1.008 -0.760 -1.34 -1.59
3  -1.254 -0.847 -1.60 -2.06
4  -1.319 -1.187 -1.34 -2.05
5  -1.335 -1.141 -1.58 -1.50
6  -0.987 -0.756 -1.22 -1.64
7  -1.290 -0.816 -2.05 -1.70
8  -1.436 -1.282 -1.53 -1.78
9  -1.491 -1.257 -1.50 -1.93
10 -1.262 -0.919 -1.64 -1.73
```

The three cross-validation objects can be plotted against each other using `kfplot()`

```
R> plot.it <- function(...) {
+    op <- par(no.readonly = TRUE)
+    on.exit(par(op))
+    par(mfrow = c(1, 3))
+    par(...)
+    what <- c("ll_mean", "ll_p_mean", "r2")
+    main <- c("Total", "Selection", "Outcome")
+    ylab <- c("OOS log-likelihood full model",
+              "OOS log-likelihood selection model",
+              expression(paste("OOS ", R^2, "")))
+    for (i in seq_along(what)) {
+      kfplot(list(kfold_10, kfold_aic, kfold), i = what[i], col = colvec,
+             main = main[i], ylab= ylab[i], xlab = "", las = 2)
```

```
+       legend("bottomleft", legend = c("fit_10", "fit_aic", "fit"),
+              fill = colvec, title = "Model", title.font = 2, bty = "n")
+     }
+   }
R> plot.it()
```

In Figure 8.1 three OOS losses (for the total model `ll_mean`, the selection `ll_p_mean` and the continuous outcome `r2`) are presented: `fit_10` has negligible higher R^2 values for the UTWers but generally performs slightly worse than the other two models.

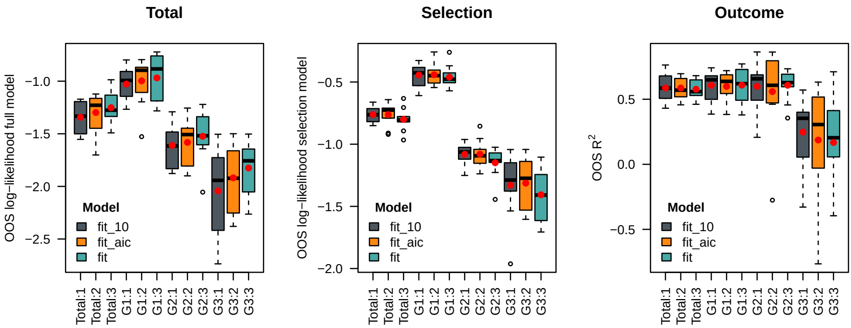

FIGURE 8.1: Model comparison by k-fold cross-validation. Note that R^2 can be negative for out-of-sample data points.

Having selected an appropriate model (say, in the name of Occam's razor, `fit_10`) the analyst would like to investigate treatment effects (TE). This can be done by

```
R> ate <- opsr_ate(fit_10, type = "unlog-response")
R> print(ate)

Treatment Effects

TE

              G1          G2          G3
T1->T2   -64.3 ***   -43.7 ***   -22.5 ***
T1->T3    61.6 ***   -21.5 ***  -117.5 ***
T2->T3   125.9 ***    22.2 ***   -95.1 ***
```

```
ATE

  T1->T2     T1->T3     T2->T3
1  -52.5 ***   12.5 **    65.0 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

where we needed to specify `type = "unlog-response"` (which is passed to `predict.opsr()`) since the outcome variable was log-transformed (log weekly kilometers traveled) before estimation. `opsr_ate()` prepares the data, returning an object of class '`opsr.ate`' and `summary.opsr.ate()` then performs the main computations, in particular a weighted paired t test for the TE (with the null that the TE is equal to 0). The method `print.summary.opsr.ate()` (i.e., `print()` called on an object of class '`summar.opsr.ate`') prints the results (method `print.opsr.ate()` redirects to `summary()` and a subsequent `print()` call).

Weights are automatically used to compute group-specific treatment effects and average treatment effects (ATE) if they were used during estimation but can be overridden by passing a new vector as `weights` argument to `opsr_ate()`.

Here we see, that the TE on the diagonal and upper triangle are negative, while we observe positive TE for `G1` (the NTWers) when switching from `T1->T3` (NTWing to UTWing), `T2->T3` (NUTWing to UTWing) and `G2` (the NUTWers) when switching from `T2->T3` (NUTWing to UTWing). Consequently, resulting ATE are positive for `T1->T3` and `T2->T3`. All effects are significantly different from 0. However, the test does not reflect parameter uncertainty.

The treatment effects can be visually summarised by

```
R> pairs(ate)
```

Figure 8.2 presents all potential pairs of regime switching. The diagonal depicts distributions of model-implied conditional expectations in any given treatment and separate by the current (factual) treatment group. The weighted mean values are shown as red numbers. The lower triangular panels compare the model-implied (predicted) outcomes of two treatment regimes, again, separate by current treatment group. The red line indicates the 45-degree line of equal outcomes while the red squares depict the weighted mean values (corresponding to the reported numbers). The upper triangular panels show (weighted) average treatment effects.

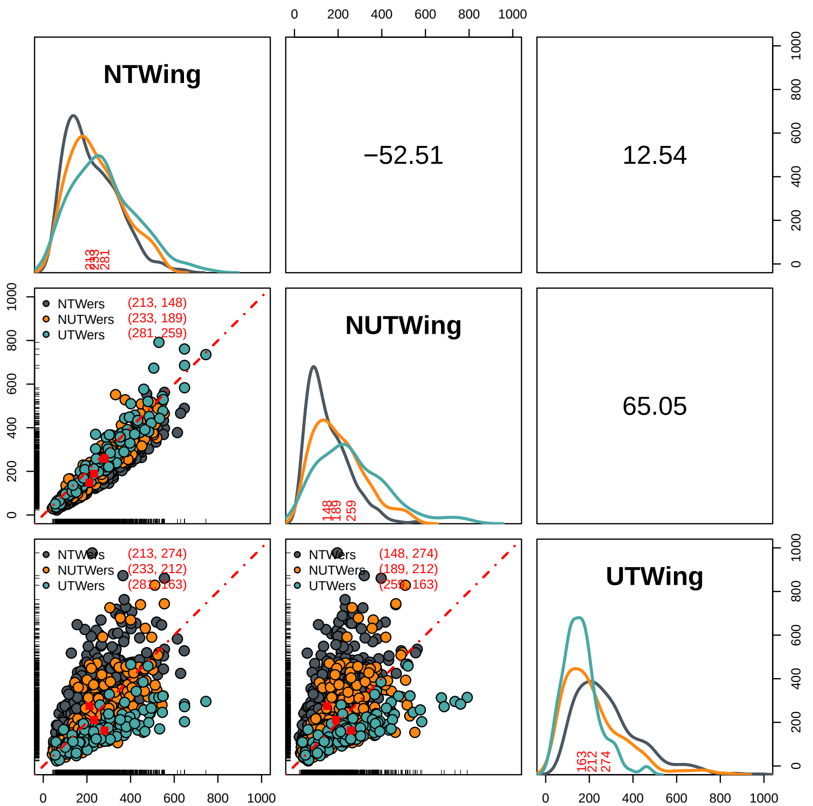

FIGURE 8.2: Pairs plot: Comparison of conditional expectations (weekly km traveled) by telework status in the lower panel. Corresponding distributions on the diagonal. Average treatment effects in the upper panel.

8.3 INVESTIGATING DIFFERENCES IN TREATMENT EFFECTS

At this point, we should highlight, that these results (based on `fit_10`) are very different from the ones presented in Chapter 7 (based on `fit_aic`), where we found negative TE and ATE only. We now further investigate, why these differences between the two models might arise. The following three hypothesis are scrutinized: 1. The large error correlation "rho3" in `fit_10` could inflate (counterfactual) weekly kilometers traveled of the NTWers and NUTWers when adopting NUTWing or UTWing via the Heckman correction term, 2. `fit_10` has fewer explanatory variables than `fit_aic` and therefore $\boldsymbol{X}_j\boldsymbol{\beta}_j$ in the two models differ, and, 3. The β coefficients are very different (and therefore $\boldsymbol{X}_j\boldsymbol{\beta}_j$ in the two models differ).

Let us first revisit the conditional expectation of the OPSR model as stated in Heimgartner and Wang (2025a)

$$\mathsf{E}[y_j \mid Z = j] = \underbrace{\boldsymbol{X}_j\boldsymbol{\beta}_j}_{\texttt{type = "Xb"}} \underbrace{- \rho_j\sigma_j \frac{\phi(\kappa_j - \boldsymbol{W}\boldsymbol{\gamma}) - \phi(\kappa_{j-1} - \boldsymbol{W}\boldsymbol{\gamma})}{\Phi(\kappa_j - \boldsymbol{W}\boldsymbol{\gamma}) - \Phi(\kappa_{j-1} - \boldsymbol{W}\boldsymbol{\gamma})}}_{\texttt{type = "correction"}}, \tag{8.1}$$

where $\boldsymbol{X}_j\boldsymbol{\beta}_j$ is the linear combination underlying the continuous outcome, κ_j and κ_{j-1} are the thresholds of the ordered probit model, $\boldsymbol{W}\boldsymbol{\gamma}$ is the linear combination modeling the latent propensity underlying the selection outcome, $\phi(\cdot)$ and $\Phi(\cdot)$ are the density and cumulative distribution function of the standard normal distribution. The fraction is the ordered probit switching regression model counterpart to the inverse Mills ratio (IMR) term of a binary switching regression model and the leading cause of selection bias (if omitted). We also see, that higher ρ_j (and/or higher σ_j) "inflates" the Heckman correction by scaling the IMR.

Similarly, the "counterfactual outcome" reflects the expected outcome under a counterfactual treatment (i.e., for $j' \neq j$) and can be expressed as

$$\mathsf{E}[y_{j'} \mid Z = j] = \boldsymbol{X}_{j'}\boldsymbol{\beta}_{j'} - \rho_{j'}\sigma_{j'} \frac{\phi(\kappa_j - \boldsymbol{W}\boldsymbol{\gamma}) - \phi(\kappa_{j-1} - \boldsymbol{W}\boldsymbol{\gamma})}{\Phi(\kappa_j - \boldsymbol{W}\boldsymbol{\gamma}) - \Phi(\kappa_{j-1} - \boldsymbol{W}\boldsymbol{\gamma})}. \tag{8.2}$$

OPSR's `predict()` method can return both components by specifying `type = "Xb"` respectively `type = "correction"` (as underbraced in Equation 8.1). Since the dependent variable was log-transformed, the above formulas return the conditional expectation in the logs. The equations for the back-transformed conditional expectations can be found in Heimgartner and Wang (2025a) and are derived in Wang and Mokhtarian (2024). However,

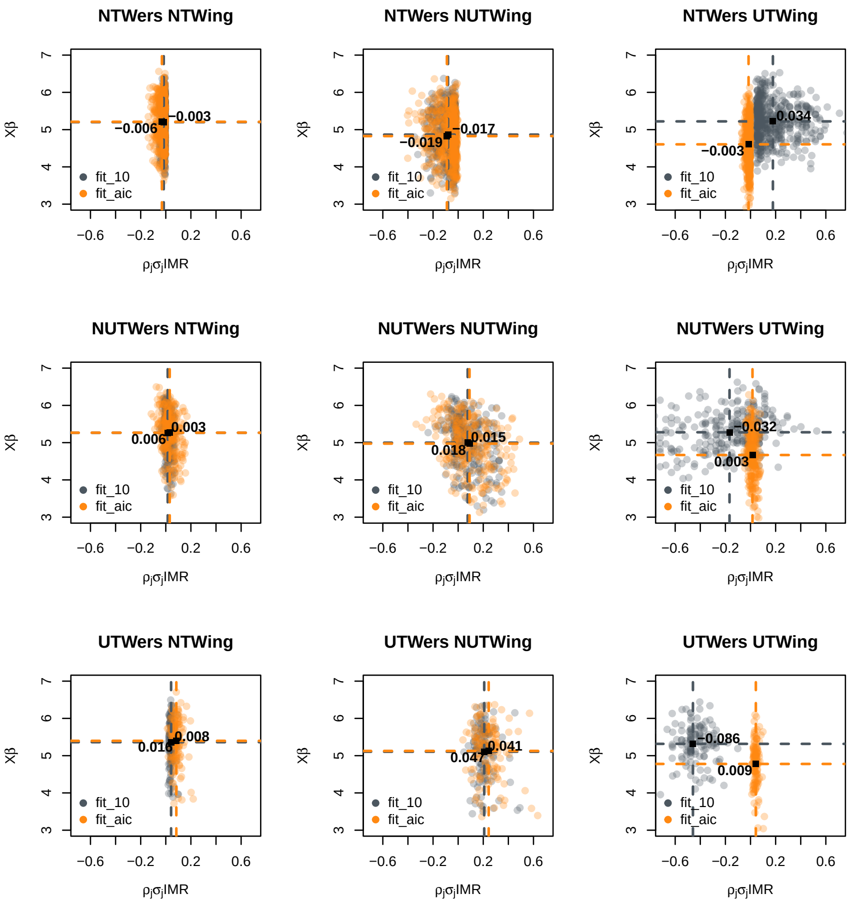

Figure 8.3: Plotting the Heckman correction term against the linear predictor. The ratio of the two mean values is printed at their intersection. Scales are shared across the facets.

in these equations, the decomposition into linear predictor and Heckman correction is no longer evident.

In Figure 8.3 we plot the Heckman correction term against the linear predictor $\boldsymbol{X}_j \boldsymbol{\beta}_j$ respectively $\boldsymbol{X}_{j'} \boldsymbol{\beta}_{j'}$. The ratio of the two mean values is printed at their intersection. We see, that 1. the correction term is small compared to $\boldsymbol{X}_j \boldsymbol{\beta}_j$ and 2. prediction differences (between `fit_aic` and `fit_10`) are because of differences in $\boldsymbol{X}_j \boldsymbol{\beta}_j$: In the last column, the horizontal dashed lines corresponding to `fit_10` are above the ones of `fit_aic` and in particular above the level of the lines in column one and two which yields the positive treatment effects oberseved in Figure 8.2.

The main motivation of OPSR is to correct for biased parameter estimates. We therefore compare the predictions of conventional regression models (i.e., fixing the "rho" coefficients at 0 during estimation) to the OPSR models.

Figure 8.4 compares the OPSR predictions (accounting for selection on unobservables) to the OLS predictions (not accounting for selection on unobservables) for both `fit_10` and `fit_aic`. For example, the first panel (NTWers NTWing) shows, that accounting for error correlation does not influence the prediction results, while panel UTWers NUTWing (row 3, column 2) indicates, that there is a selection bias, underestimating the weekly kilometers traveled of UTWers when NUTWing. Meanwhile, the selection bias is comparable for `fit_10` and `fit_aic`. Interestingly, the two models seem to agree on the selection bias with the exception of NTWers UTWing and NUTWers UTWing (column 3, row 1 and 2), when `fit_10` suddenly suggests a sizable selection bias – considerably underestimating the weekly distance traveled. The treatment effects of the four models are summarized in Table 8.1 where the reader can confirm, that resulting treatment effects are very different. However, the OLS model `fit_aic_nocor` (i.e., the model with the same specification $\boldsymbol{X}_j \boldsymbol{\beta}_j$ as `fit_aic`) agrees with the direction of the treatment effect, despite generally underestimating it. Similarly, `fit_10_nocor` shows negative TE and ATE and the numbers are similar to `fit_aic_nocor`. Again, the reversed TE for `fit_10` seem to be the clear exception.

This evidence suggests, that it is not actually the direct influence of the error correlation via the Heckman correction term but the indirect influence via the β coefficients that leverages the predictions and thus treatment effect computations. And if we only have few explanatory variables, then the error correlation might have a bigger influence on these estimates. Under certain conditions, OPSR models might become poorly identified, suggesting extreme selection bias (as does `fit_10` in our case). Taking

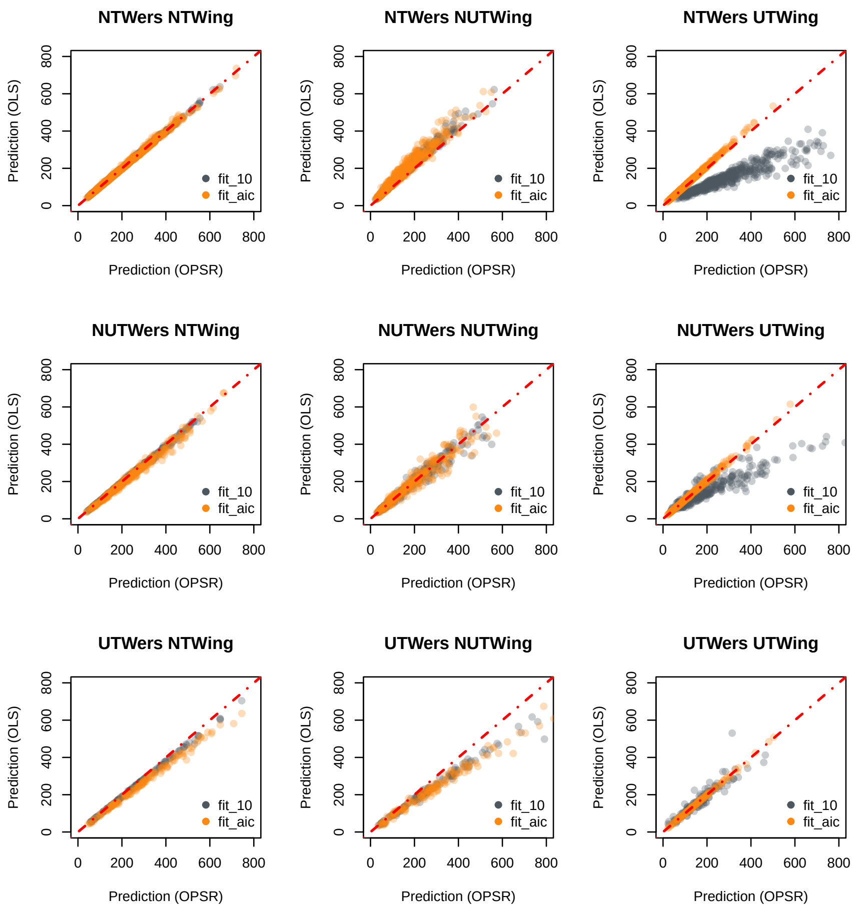

FIGURE 8.4: The influence of accounting for error correlation on predictions: Plotting the OPSR predictions against the OLS predictions.

Model	Regime switch	NTWers	NUTWers	UTWers	ATE
`fit_aic`	NTWing→NUTWing	-69.746	-53.592	-28.677	-59.242
	NTWing→UTWing	-95.295	-103.763	-139.056	-104.223
	NUTWing→UTWing	-25.549	-50.171	-110.379	-44.982
`fit_aic_nocor`	NTWing→NUTWing	-38.244	-40.881	-47.309	-40.322
	NTWing→UTWing	-87.925	-86.903	-107.314	-90.645
	NUTWing→UTWing	-49.681	-46.022	-60.005	-50.322
`fit_10`	NTWing→NUTWing	-64.282	-43.678	-22.466	-52.510
	NTWing→UTWing	61.644	-21.512	-117.519	12.535
	NUTWing→UTWing	125.925	22.165	-95.053	65.046
`fit_10_nocor`	NTWing→NUTWing	-39.895	-37.452	-46.825	-40.329
	NTWing→UTWing	-74.403	-76.101	-100.380	-78.841
	NUTWing→UTWing	-34.508	-38.649	-53.555	-38.512

TABLE 8.1: Treatment effect comparison. `nocor` implies the regular OLS fit with "rho" fixed at 0.

all this evidence into account, we would still trust the insights based on `fit_aic` (as discussed in Chapter 7) the most.

Identification issues of Heckman-type selection models have received considerable attention in the literature (e.g., Puhani, 2000), investigating conditions under which model estimation becomes challenging. In Monte Carlo simulation studies, the performance of LIML and FIML estimators are then usually compared. The main condition discussed is weak exclusion-restrictions (weak instruments; leading to colinearity between the IMR and $\boldsymbol{X}$) as elaborated in Chiburis and Lokshin (2007). Huismans *et al.* (2022) discuss maximum likelihood estimation and parameter identification (for a Heckman-selection model with ordered outcomes) and state that in mixture models, the likelihood function may have multiple local maximums and large flat regions and suggest testing different starting values (in our case, both `fit_10` and `fit_aic` converge to the same optimum if we set starting values to 0, -1 for "kappa1", 1 for "kappa2" and 1 for the "sigmas"). Since the IMR is technically a regressor, we speculate, that the limited variability (as observed in Figure 8.3, in particular for UTWing, column 3) could also yield poor identification.

8.4 SUMMARY

OPSRtools introduced in this article contains estimation and post-estimation routines for the **OPSR** R-package, allowing modelers to efficiently specify, select and evaluate ordered probit switching regression models. Treatment effects are easily computed, summarised and visualized. We further investigated model-implied differences in treatment effects and why they might arise. Visualizations are proposed to scrutinize the influence of the Heckman correction term on predictions and thus treatment effects. However, we find that in our case study, treatment effects do not mainly differ because of this correction but because OPSR yields different (and hopefully unbiased) parameter estimates. We also raise concerns about the stability of such models and potential identification issues. It is left for future research to propose methods detecting poor identification and its leading cause.

9

SUMMARY

In the end, everything is endogenous! If it's not, it's not the end.

The aim of this final chapter is to summarize the main contributions of this thesis, to reflect on their relevance for science and society, and to outline directions for future work.

9.1 MAIN FINDINGS

In Chapter 1, I outlined a number of research questions that underlie this thesis. Here, I summarize the key results and reflect to what extent the research questions have been answered.

The research questions posed at the outset of this thesis were

RQ1: How did telework adoption change over the course of the pandemic in Switzerland?

RQ2: Who are the teleworkers? Who has the option to telework, who wants to telework and how much?

RQ3: How can telework be managed? Can employers entice employees back to the office once lockdown measures are lifted?

RQ4: What is the impact of telework on transport demand?

Chapter 2 analyzed long-term mobility changes during and after COVID-19, using the MOBIS-Covid panel data. While temporary shifts in mode use occurred (e.g., increased walking and cycling) mode preferences largely returned to pre-pandemic patterns. Overall, the pandemic did not induce a structural break in underlying mode share preferences. The lasting legacy of the pandemic, is higher telework adoption which seems to affect mobility indirectly via sociodemographic segmentation. In light of RQ4, and in accordance with Sallard (2024), telework does only minimally affect modal splits. This is important, because (relative) priority of infrastructure projects does not need to be reevaluated as a consequence.

Chapter 3 examined how survey response burden affects response rates, distinguishing the impacts of recruitment efforts and incentives. The burden had a more negative effect than previously anticipated. While recruitment raised overall response levels, only incentives mitigated the steep decline.

Chapter 4 analyzed the rise of telework in Switzerland post-COVID, using a large-scale survey and two stated preference experiments. It found that while telework increased by 15 percentage points, a notable gap remained between those able to telework and those actually doing so. Employer constraints limited broader adoption (RQ1). No direct shift from public transport to car ownership was observed, even at high telework frequencies (RQ4). Meanwhile, the share of teleworkers varies over the weekdays with Mondays and Fridays being the most prominent to telework. As a consequence, transport network loads vary over the weekdays (RQ4). The dataset offers a valuable basis for future research on hybrid work and its impact on mobility tool ownership beyond the scope of this thesis.

Chapter 5 explored how hybrid work policies influence telework frequency, emphasizing the role of incentives. It found that salary adjustments were the most effective in encouraging telework, but deviations from baseline preferences were hard to achieve (RQ3). The results suggest that returning employees to the office would imply substantial utility losses. Meanwhile, broader societal benefits of telework, such as reduced vehicle miles, are overlooked during labor market negotiations. This potentially leads to suboptimal telework adoption.

Chapter 6 introduced the **OPSR** R-package, a tool for addressing selection bias in ordinal treatments using endogenous switching regression. The implementation offers a fast, memory-efficient and easy-to-use API, leveraging C++ for parallelized log-likelihood computation. It also handles log-transformed outcomes.

OPSR is the enabler of the analysis at the heart of the thesis in Chapter 7. There, the effects of telework on transport demand were examined, finding that telework leads to a significant reduction in weekly kilometers traveled, with an estimated 16% reduction compared to a no-telework scenario. The analysis showed that rebound effects from telework are minimal and do not offset the reduction in travel. The study highlighted that the true treatment effects of telework are likely underestimated if selection bias is not accounted for. Further, counterfactual travel distances for teleworkers are much higher than observed for non-teleworkers. Overall, the results support the narrative that telework reduces transport demand substantially (RQ4).

RQ2 was only implicitly and partially answered in Chapter 7, modeling telework frequency as part of the OPSR approach. However, the discussion evolved around treatment effects and parameter estimates were not commented in light of RQ2. Work differentiating between feasibility (can), option (may), and choice (want) as in Heimgartner and Axhausen (2023e) or Heimgartner and Axhausen (2023a) are not part of this thesis. Further, as mentioned throughout the text, modeling telework frequency is a well-researched subject. What my work highlights, is, that teleworkers are a particularly mobile group (i.e., with higher counterfactual weekly distance traveled than other teleworkers or non-teleworkers) and tend to have longer commutes. While there is evidence that teleworkers accept longer commutes (Ravalet and Rérat, 2019; de Vos *et al.*, 2018) it could also be the other way round, i.e., that longer commutes are a motive to telework more.

Chapter 8 introduced **OPSRtools**, an R-package designed to support the estimation and post-estimation of ordered probit switching regression models (developed as part of the analysis in the preceeding chapter). The tools facilitate model selection, cross-validation, treatment effect computation, and visualization. The study also explored how different treatment effects arise and highlighted the role of the Heckman correction term in model predictions. The findings suggest that treatment effect differences are largely due to unbiased parameter estimates from OPSR rather than the correction term itself. Potential concerns about model stability and identification issues are left for future research.

9.2 RELEVANCE OF THE THESIS TO SCIENCE AND SOCIETY

While the methods used in this thesis are old, their implementation in statistical environments were limited. At the same time, understanding when and why selection bias might occur could be complicated by a mostly technical discussion surrounding the topic. This thesis demonstrates, that sometimes, more complex econometric models are justified arising from intricate error structures of the underlying processes and the need to account for error correlation. Results and thereby policy implications can be widely different or even suggest opposite directions of effect. The OPSR modeling frame is limited to an ordinal selection and continuous outcome process (see Section 9.3 for a more in-depth discussion). However, such treatment situations can readily occur and therefore **OPSR** is of potential use in various contexts and across disciplines.

The transport sector contributes 15% of global greenhouse gas emissions (IPCC, 2022), with emissions at 31% being significantly higher in Switzerland (BAFU, 2024). Meanwhile, reducing it through policies such as road pricing or fuel taxes is unpopular. Similarly, being mobile yields great utility and behavioral adjustments (e.g., reducing leisure travel) are difficult. The thesis provides evidence, that telework can be an effective tool to reduce transport demand. At the same time, foregone commutes imply a substantial utility gain. However, employers would like to see their workforce returning to the office more frequently. The elephant in the room is feared productivity losses. While evidence on such productivity losses is contested, I claim, that potential foregone profits are nowhere near telework's utility gains (see Chapter 5). Depending on the labor market situation, employers could nevertheless be able to demand employees back to the office (having realized that a free lunch won't suffice). In spirit of the efficient market hypothesis, the resulting labor market equilibrium is suboptimal, since it does not reflect ("price in") broader societal benefits such as reduced emissions, congestion, etc. In that regard, I hope that telework won't be a pill not taken, and that politicians recognize and protect its value (e.g., through a right to telework).

9.3 LIMITATIONS AND FUTURE WORK

The final paragraphs shall be used to criticize my own work and hint to avenues for future research. I do so in chronological order.

9.3.1 *Direct critizism and resulting avenues*

In the MMDCEV model of Chapter 2 telework status is treated as an exogenous factor variable. Further, it was measured during a particular point in time and could have changed since measurement (leading to measurement error). Both could imply endogeneity problems (since telework could be correlated with the error term) and bias estimates. Since the outcome is discrete-continuous, endogenous switching regression formulations, to my knowledge, don't exist. The MOBIS-Covid data would also lend itself to conduct rigorous time-series analysis (choosing another outcome) and properly test for structural breaks.

An obvious data limitation underlying Chapter 3, is, that the form and level of the incentive was not recorded. It would be valuable to know for survey work, in how far response rates depend on the level of the incentive.

Similarly, the estimated relation between response burden and response rates hold for surveys conducted at the institute. Other research groups are encouraged to score their survey instruments and contribute the data to the **responseRateAnalysis** repository (Heimgartner, 2024c). The model could then be extended, to control for the institution and potentially other context.

Chapter 4 discussed at length the difficulty to conduct a stated preference experiment investigating mobility tool ownership choices. The underlying problem is so complex that I question, A, that the actual choice can be reliably depicted in a digital context (e.g., the full universe of mobility tools with accurate cost implications) and B (given A), that the respondent will consume all the information and make an educated choice. Third (given A and B), it would be challenging to model the simultaneous choice, since the more realistic A, the more degrees of freedom (e.g., a consumer can choose how many cars to own, what brand, what fuel type, engine size, etc.).

The data collected was by no means exhausted in this (and related) work. Researchers are encouraged to skim through the available variables in Appendix A.3.3. For example, with the **snndata**, researchers could investigate the role of personality traits on telework adoption. Similarly, replicating Singh *et al.* (2013) with the new data would be an interesting exercise.

In Chapter 5, we estimated separate MNL and OL models for the work arrangement and telework frequency choice. However, in the SP, the choice was made simultaneously and probably should be modeled as such (once again, accounting for potential error correlation between the two simultaneous processes). In spirit of this thesis, an SP can be thought of as an information treatment where the information is usually exogenous. However, in the SP at hand, the information treatment underlying the frequency choice was self-selected (warm regards from Heckman!).

As realized in Chapter 6, modeling multiple processes simultaneously is a very interesting problem. The family of conditional mixed-process models (Roodman, 2011) is well suited for such problems. However, while the multivariate normal (underlying CMP as well as OPSR) is a convenient choice, it is only one possible error distribution. As with any probability model, the assumed error distribution defines the structure of the resulting likelihood function and dictates the whole implementation. Optimally, the modeler would test different distributions and identify the most suitable one. While, first, such models are relatively hard to implement – I, second, am not aware of suitable diagnostics tools to investigate such distributional assumptions (at least not in an absolute sense, since most errors are latent).

Copula modeling (Hofert *et al.*, 2018, in particular Chapter 6) could provide an interesting alternative, but to my awareness, a uniform modeling framework is not readily available – at least not in R.

The OPSR specification underlying Chapter 7 includes commute distance as an explanatory variable (both in the selection and outcome process). Endogeneity (because of simultaneity) could be a problem.

It would also be interesting to leverage the panel nature of the TimeUse+ data and compare a panel regression approach to OPSR.

The last chapter (Chapter 8) did not identify the exact cause of the identification problems. Future work could extend **OPSRtools** with tools to detect poorly identified model specifications.

Lastly, this thesis exclusively looked at the Swiss case and external validity beyond the country boarder is to be questioned. However, with the toolchain provided, an OPSR analysis for a new study context can be readily conducted. Once census data incorporates more telework related questions scholars are encouraged to repeat the analysis.

9.3.2 *LOL value proposition*

Let's assume there are M environments for statistical computing and N models and that each model is implemented in each language (i.e., MxN implementations). Every environment (and sometimes every author) has it's own idea how the modeling pipeline should be implemented. But conventionally, there are three steps involved

1. An API to specify a model (in R usually a formula interface).
2. Input parsing, checking and preparation of the model matrices.
3. The inputs are then passed to a basic computation engine (fitter function), ultimately returning the estimated parameters.

While 1. and 2. are relatively easy, 3. can be quite an effort, especially when speed and memory considerations play a role and a language such as C++ is chosen.

However, if a common interface from 2. to 3. would exist and modelers would agree on a language of likelihood (LOL) the MxN problem would collapse to an (almost) $M + N$ problem (as any environment could leverage the same implementation of the main computation engine). A similar value proposition (arguing that Julia should be the language of choice) was made in Roodman (2024). The *Stan* project (Stan Development Team, 2024) is somewhat similar to this idea and covers the Bayesian case.

A

APPENDIX

A.1 MODEL COMPARISON

The final model from Section 7.5.3 is compared to other benchmark models (the null, full and AIC-preferred model) along with conventional goodness of fit indicators.

	Null model	Full model	Model AIC	Final model
Telework allowed (s)		0.86 (0.18)***	0.82 (0.16)***	0.82 (0.16)***
Teleworkability (s)		0.25 (0.04)***	0.26 (0.03)***	0.25 (0.04)***
July (s)		0.73 (0.61)		
August (s)		0.59 (0.57)		
Start month (ref: Jan.)				
September (s)		0.04 (0.58)		
October (s)		0.25 (0.56)		
November (s)		0.39 (0.57)		
December (s)		0.23 (0.58)		
Log commute km (s)		0.09 (0.08)	0.11 (0.08)	0.12 (0.08)
Age (s)		0.01 (0.01)*	0.01 (0.01)*	0.01 (0.01)*
Has dogs (s)		0.52 (0.19)**	0.63 (0.19)***	0.63 (0.19)***
Driver license (s)		0.34 (0.27)	0.26 (0.27)	0.25 (0.27)
Higher education (s)		−0.13 (0.16)		
Fixed workplace (s)		−0.50 (0.20)*	−0.41 (0.20)*	−0.40 (0.20)*
Grocery shopper (s)		−0.12 (0.15)		
4001 - 8000 CHF (s)		−0.69 (0.35)*	−0.62 (0.32)	−0.63 (0.33)
8001 - 12000 CHF (s)		−0.88 (0.35)*	−0.80 (0.31)*	−0.81 (0.32)*
HH income (ref: <4000 CHF)				
12001 - 16000 CHF (s)		−1.06 (0.37)**	−0.87 (0.32)**	−0.87 (0.33)**
16000+ CHF (s)		−0.41 (0.39)	−0.23 (0.33)	−0.23 (0.35)
HH size (s)		0.29 (0.10)**	0.23 (0.09)*	0.23 (0.09)**
Clerical (s)		0.25 (0.16)	0.20 (0.13)	0.20 (0.13)
Craft and trades (s)		−0.24 (0.36)		
ISCO				
Managers (s)		−0.29 (0.18)	−0.26 (0.15)	−0.27 (0.15)
Plant and machine (s)		−0.53 (0.69)		
Professionals (s)		0.11 (0.18)		
Service and sales (s)		0.04 (0.19)		
Agri, forest and fishery (s)		0.39 (0.40)	0.21 (0.33)	0.16 (0.37)

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Table A.1 – *Continued from previous page*

	Null model	Full model	Model AIC	Final model
Technicians (s)		−0.16 (0.25)		
Married (s)		−0.02 (0.17)		
Number of children (s)		−0.18 (0.13)	−0.14 (0.11)	−0.14 (0.11)
Frequent online shopper (s)		0.13 (0.14)	0.09 (0.13)	0.09 (0.13)
Parking home (s)		0.60 (0.37)	0.50 (0.38)	0.50 (0.39)
Parking work (s)		−0.19 (0.13)	−0.16 (0.13)	−0.17 (0.14)
Permanent work contract (s)		0.38 (0.31)	0.34 (0.27)	0.34 (0.27)
Tenant (s)		−0.09 (0.15)		
Suburban (s)		−0.29 (0.24)		
Urban (s)		−0.12 (0.21)		
Res. loc. (ref: Rural)				
Male (s)		−0.29 (0.19)	−0.25 (0.14)	−0.25 (0.14)
Works in shifts (s)		−0.17 (0.28)		
Swiss (s)		−0.35 (0.19)	−0.31 (0.16)	−0.33 (0.17)
Vacation during study (s)		−0.09 (0.15)		
Workload (s)		0.03 (0.04)		
Has kids below 12 (s)		0.04 (0.21)		
Intercept (01)	5.17 (0.03)***	3.06 (0.35)***	2.89 (0.30)***	2.89 (0.31)***
July (01)		0.42 (0.24)	0.38 (0.24)	0.38 (0.24)
August (01)		0.24 (0.24)	0.19 (0.23)	0.19 (0.23)
Start month (ref: Jan.)				
September (01)		0.27 (0.25)	0.27 (0.23)	0.27 (0.23)
October (01)		0.28 (0.24)	0.29 (0.23)	0.29 (0.23)
November (01)		0.42 (0.25)	0.40 (0.24)	0.40 (0.24)
December (01)		0.27 (0.24)	0.25 (0.22)	0.25 (0.23)
Log commute km (01)		0.57 (0.04)***	0.58 (0.04)***	0.58 (0.04)***
Age (01)		0.00 (0.00)		
Has dogs (01)		0.11 (0.08)	0.18 (0.07)*	0.18 (0.07)*
Driver license (01)		0.18 (0.09)*	0.20 (0.09)*	0.20 (0.09)*
Higher education (01)		−0.03 (0.06)		
Fixed workplace (01)		−0.17 (0.11)	−0.15 (0.09)	−0.15 (0.09)
Grocery shopper (01)		0.07 (0.06)	0.08 (0.06)	0.08 (0.06)
4001 - 8000 CHF (01)		−0.08 (0.10)		
8001 - 12000 CHF (01)		0.02 (0.10)		
HH income (ref: <4000 CHF)				
12001 - 16000 CHF (01)		−0.10 (0.12)		
16000+ CHF (01)		−0.00 (0.19)		
HH size (01)		0.02 (0.04)		
Married (01)		−0.02 (0.07)		
Number of children (01)		−0.10 (0.04)*	−0.08 (0.03)**	−0.08 (0.03)**
Frequent online shopper (01)		0.04 (0.05)		
Parking home (01)		−0.09 (0.11)		
Parking work (01)		0.13 (0.05)**	0.14 (0.05)**	0.14 (0.05)**
Permanent work contract (01)		0.25 (0.10)*	0.29 (0.10)**	0.29 (0.10)**

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Table A.1 – *Continued from previous page*

	Null model	Full model	Model AIC	Final model
Tenant (01)		0.03 (0.06)		
Suburban (01)		−0.04 (0.08)		
Urban (01)		−0.13 (0.07)		
Res. loc. (ref: Rural)				
Male (01)		0.14 (0.06)*	0.17 (0.06)**	0.17 (0.06)**
Works in shifts (01)		−0.12 (0.09)	−0.09 (0.07)	−0.09 (0.07)
Swiss (01)		−0.02 (0.06)		
Vacation during study (01)		−0.06 (0.07)	−0.07 (0.07)	−0.07 (0.07)
Workload (01)		0.02 (0.01)	0.02 (0.01)	0.02 (0.01)
Has kids below 12 (01)		0.01 (0.08)		
Intercept (02)	5.10 (0.04)***	3.07 (0.56)***	3.28 (0.27)***	3.27 (0.27)***
July (02)		0.37 (0.22)		
August (02)		0.47 (0.23)*		
Start month (ref: Jan.)				
September (02)		0.23 (0.26)		
October (02)		0.31 (0.22)		
November (02)		0.24 (0.20)		
December (02)		0.11 (0.22)		
Log commute km (02)		0.65 (0.04)***	0.69 (0.04)***	0.69 (0.04)***
Age (02)		−0.00 (0.00)		
Has dogs (02)		0.13 (0.08)	0.14 (0.07)	0.14 (0.07)
Driver license (02)		0.09 (0.16)		
Higher education (02)		−0.04 (0.07)		
Fixed workplace (02)		−0.22 (0.10)*	−0.28 (0.10)**	−0.28 (0.10)**
Grocery shopper (02)		−0.14 (0.08)	−0.12 (0.07)	−0.12 (0.07)
4001 - 8000 CHF (02)		−0.12 (0.18)		
8001 - 12000 CHF (02)		−0.12 (0.18)		
HH income (ref: <4000 CHF)				
12001 - 16000 CHF (02)		−0.25 (0.21)		
16000+ CHF (02)		−0.23 (0.19)		
HH size (02)		0.07 (0.05)	0.07 (0.03)*	0.07 (0.03)*
Married (02)		−0.10 (0.10)	−0.11 (0.07)	−0.11 (0.07)
Number of children (02)		−0.05 (0.06)		
Frequent online shopper (02)		0.05 (0.07)		
Parking home (02)		0.05 (0.13)		
Parking work (02)		−0.06 (0.06)	−0.08 (0.06)	−0.08 (0.06)
Permanent work contract (02)		0.01 (0.13)		
Tenant (02)		−0.05 (0.07)		
Suburban (02)		−0.05 (0.11)		
Urban (02)		−0.11 (0.09)		
Res. loc. (ref: Rural)				
Male (02)		0.12 (0.07)	0.10 (0.07)	0.10 (0.07)
Works in shifts (02)		−0.27 (0.12)*	−0.25 (0.11)*	−0.25 (0.11)*
Swiss (02)		0.08 (0.11)		

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Table A.1 – *Continued from previous page*

	Null model	Full model	Model AIC	Final model
Vacation during study (02)		0.14 (0.08)	0.12 (0.07)	0.12 (0.07)
Workload (02)		0.02 (0.02)	0.01 (0.02)	0.01 (0.02)
Has kids below 12 (02)		−0.10 (0.10)	−0.19 (0.08)*	−0.19 (0.08)*
Intercept (03)	4.89 (0.06)***	2.24 (0.87)*	2.30 (0.44)***	2.71 (0.47)***
July (03)		0.14 (0.32)		
August (03)		−0.25 (0.23)		
Start month (ref: Jan.)				
September (03)		0.20 (0.22)		
October (03)		−0.05 (0.21)		
November (03)		0.20 (0.22)		
December (03)		0.31 (0.27)		
Log commute km (03)		0.43 (0.06)***	0.43 (0.06)***	0.48 (0.06)***
Age (03)		0.00 (0.01)		
Has dogs (03)		0.13 (0.19)		
Driver license (03)		0.50 (0.26)	0.39 (0.21)	
Higher education (03)		0.16 (0.15)	0.16 (0.11)	0.21 (0.10)*
Fixed workplace (03)		−0.16 (0.21)		
Grocery shopper (03)		−0.04 (0.12)		
4001 - 8000 CHF (03)		0.19 (0.18)		
8001 - 12000 CHF (03)		0.36 (0.18)*		
HH income (ref: <4000 CHF)				
12001 - 16000 CHF (03)		0.15 (0.25)		
16000+ CHF (03)		0.29 (0.24)		
HH size (03)		0.16 (0.07)*	0.13 (0.03)***	0.16 (0.04)***
Married (03)		−0.46 (0.15)**	−0.39 (0.11)***	−0.34 (0.12)**
Number of children (03)		−0.03 (0.08)		
Frequent online shopper (03)		0.22 (0.22)	0.34 (0.17)*	0.39 (0.23)
Parking work (03)		0.17 (0.11)	0.26 (0.11)*	
Permanent work contract (03)		−0.19 (0.32)		
Tenant (03)		0.09 (0.13)		
Suburban (03)		−0.63 (0.21)**	−0.48 (0.19)*	−0.53 (0.20)**
Urban (03)		−0.70 (0.18)***	−0.54 (0.19)**	−0.56 (0.20)**
Res. loc. (ref: Rural)				
Male (03)		0.10 (0.14)		
Swiss (03)		0.21 (0.16)	0.24 (0.18)	
Vacation during study (03)		0.03 (0.12)		
Workload (03)		0.04 (0.03)	0.07 (0.03)*	0.06 (0.03)*
Has kids below 12 (03)		0.09 (0.17)		
Kappa 1	0.15 (0.04)***	2.75 (1.17)*	2.40 (0.77)**	2.39 (0.76)**
Kappa 2	1.06 (0.05)***	4.00 (1.17)***	3.62 (0.77)***	3.60 (0.75)***
Sigma 1	0.72 (0.03)***	0.39 (0.02)***	0.39 (0.02)***	0.39 (0.02)***
Sigma 2	0.71 (0.03)***	0.38 (0.04)***	0.41 (0.04)***	0.41 (0.04)***
Sigma 3	0.65 (0.04)***	0.41 (0.12)***	0.43 (0.04)***	0.46 (0.06)***
Rho 1		0.19 (0.54)	0.18 (0.42)	0.19 (0.42)

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Table A.1 – *Continued from previous page*

	Null model	Full model	Model AIC	Final model
Rho 2		0.44 (0.13)***	0.50 (0.10)***	0.50 (0.10)***
Rho 3		0.49 (0.73)	0.08 (0.26)	0.20 (0.40)
AIC	3601.27	2207.65	2159.39	2172.10
BIC	3639.50	2929.24	2513.02	2511.40
Log Likelihood	−1792.64	−952.82	−1005.70	−1015.05
Pseudo R^2 (EL)	0.12	0.30	0.31	0.31
Pseudo R^2 (MS)	−0.00	0.20	0.21	0.21
R^2 (total)	0.02	0.64	0.62	0.61
R^2 (1)	−0.00	0.64	0.64	0.64
R^2 (2)	−0.00	0.68	0.65	0.66
R^2 (3)	−0.00	0.46	0.36	0.32
Num. obs.	879	879	879	879

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1;
s = structural components;
o1 = outcome 1 (NTW);
o2 = outcome 2 (NUTW);
o3 = outcome 3 (UTW)

TABLE A.1: Model comparison.

A.2 COMPUTATIONAL DETAILS

The results in this thesis were obtained using R 4.4.0. R itself and all packages used are available from the Comprehensive R Archive Network (CRAN) at https://CRAN.R-project.org/.

apollo 0.3.3, **gridExtra** 2.3, **gridGraphics** 0.5.1, **kableExtra** 1.4.0, **knitr** 1.48, **MASS** 7.3.60, **mixl** 1.3.3, **mvtnorm** 1.2.5, **ordinal** 2023.12.4.1, **sampleSelection** 1.2.12, **tableone** 0.13.2, **texreg** 1.39.4, **TraMineR** 2.2.11.

Each chapter is organized as a separate R-package, available on request from https://github.com/phd-thesis-heimgartner.

myThesis 0.0.0.9000, **mpp** 0.0.0.9000, **mppData** 0.0.0.9000, **responseRateAnalysis** 0.1.0, **datapap** 0.1.0, **trb24** 0.0.0.9005, **OPSR** 0.2.0, **TUplus** 0.1.2, **TWTE** 0.1.1.9000, **OPSRtools** 0.0.0.9000.

A.3 R REFERENCE MANUALS

A.3.1 OPSR *reference manual*

`OPSR-package` *OPSR: Ordered Probit Switching Regression*

Description

Estimates ordered probit switching regression models - a Heckman type selection model with an ordinal selection and continuous outcomes. Different model specifications are allowed for each treatment/regime. For more details on the method, see Wang and Mokhtarian (2024) or Chiburis and Lokshin (2007).

Author(s)

Maintainer: Daniel Heimgartner `<d.heimgartners@gmail.com>` (ORCID) [copyright holder]

Authors:

- Xinyi Wang `<xinyi174@mit.edu>` (ORCID)

See Also

Useful links:

- `https://github.com/dheimgartner/OPSR`
- Report bugs at `https://github.com/dheimgartner/OPSR/issues`

`anova.opsr` *ANOVA for OPSR Model Fits*

Description

Conducts likelihood ratio tests for one or more OPSR model fits.

Usage

```
## S3 method for class 'opsr'
anova(object, ...)
```

Arguments

`object`	an object of class `"opsr"`.
`...`	additional objects of class `"opsr"`. See also the 'Details' section.

Details

If only a single object is passed then the model is compared to the null model (`opsr_null_model`). If more than one object is specified, a likelihood ratio test is conducted for each pair of neighboring models. It is conventional to list the models from smallest to largest, but this is up to the user.

Value

An object of class `"anova.opsr"`.

See Also

`stats::anova`, `print.anova.opsr`

Examples

```
sim_dat <- opsr_simulate()
dat <- sim_dat$data
model <- ys | yo ~ xs1 + xs2 | xo1 + xo2
```

```
fit <- opsr(model, dat)
fit_null <- opsr_null_model(fit)
fit_intercept <- update(fit, ~ . | 1)

anova(fit)
anova(fit_null, fit_intercept, fit)
```

`extract,opsr-method` *Extract Method for OPSR Model Fits*

Description

This is the main method called when using functions from the `texreg-package`.

Usage

```
## S4 method for signature 'opsr'
extract(
  model,
  beside = FALSE,
  include.structural = TRUE,
  include.selection = TRUE,
  include.outcome = TRUE,
  include.pseudoR2 = FALSE,
  include.R2 = FALSE,
  repeat.gofs = FALSE,
  ...
)
```

Arguments

`model` an object of class `"opsr"`.

`beside` if `TRUE`, prints structural, selection and outcome coefficients side-by-side.

`include.structural`
whether or not structural coefficients should be printed.

`include.selection`
whether or not selection coefficients should be printed.

`include.outcome`
: whether or not outcome coefficients should be printed.

`include.pseudoR2`
: whether or not the pseudo R2 statistic for the selection component should be printed. See also the 'Details' section.

`include.R2`
: whether or not the R2 statistic for the outcome components should be printed.

`repeat.gofs`
: if `beside = TRUE` whether or not to repeat the gofs.

`...`
: additional arguments passed to `summary.opsr`.

Details

The `extract` method is called internally. Higher-level functions from the `texreg-package` pass arguments via `...` to `extract`.

`include.pseudoR2` reports both the "equally likely" (EL) and "market share" (MS) pseudo R2.

Value

A `texreg-class` object representing the statistical model.

See Also

`texreg-package`, `texreg::texreg`, `texreg::screenreg` and related functions.

Examples

```
sim_dat <- opsr_simulate()
dat <- sim_dat$data
model <- ys | yo ~ xs1 + xs2 | xo1 + xo2
fit <- opsr(model, dat)
fit_null <- opsr_null_model(fit)
fit_intercept <- update(fit, ~ . | 1)

texreg::screenreg(fit)
texreg::screenreg(fit, beside = TRUE)
texreg::screenreg(fit, beside = TRUE, include.pseudoR2 = TRUE,
                  include.R2 = TRUE)
texreg::screenreg(list(fit_null, fit_intercept, fit))
```

loglik_cpp	*Interface to C++ Log-Likelihood Implementation*

Description

This is the main computation engine wrapped by `opsr.fit`.

Usage

```
loglik_cpp(theta, W, X, Y, weights, nReg, nThreads)
```

Arguments

`theta`	named coefficient vector as parsed from formula interface `opsr`.
`W`	list of matrices with explanatory variables for selection process for each regime.
`X`	list of matrices with expalanatory varialbes for outcome process for each regime.
`Y`	list of vectors with continuous outcomes for each regime.
`weights`	vector of weights. See also `opsr`.
`nReg`	integer number of regimes.
`nThreads`	number of threads to be used by `OpenMP` (should be max. `nReg`).

Value

Numeric vector of (weighted) log-likelihood contributions.

See Also

`opsr.fit`, `loglik_R`

`loglik_R`	*R-based Log-Likelihood Implementation*

Description

R-based Log-Likelihood Implementation

Usage

```
loglik_R(theta, W, X, Y, weights, nReg, ...)
```

See Also

`loglik_cpp`, `opsr.fit`

`model.frame.opsr`	*Extracting the Model Frame from OPSR Model Fits*

Description

Extracting the Model Frame from OPSR Model Fits

Usage

```
## S3 method for class 'opsr'
model.frame(formula, ...)
```

Arguments

`formula`	an object of class `"opsr"`.
`...`	a mix of further arguments such as `data`, `na.action` or `subset`, passed to the default method.

Value

A `data.frame` containing the variables used in `formula$formula`.

See Also

`stats::model.frame`

`model.matrix.opsr` *Construct Design Matrices for OPSR Model Fits*

Description

Construct Design Matrices for OPSR Model Fits

Usage

```
## S3 method for class 'opsr'
model.matrix(object, data, .filter = NULL, ...)
```

Arguments

`object`	an object of class `"opsr"`.
`data`	a data frame containing the terms from `object$formula`. Passed to `model.frame.opsr`. Can be omitted.
`.filter`	used internally in `predict.opsr` for counterfactual predictions.
`...`	further arguments passed to or from other methods.

Value

A list of lists with the design matrices `W` (selection process) and `X` (outcome process). Both of these lists have `object$nReg` elements (a separate design matrix for each regime).

See Also

`model.frame.opsr`, `stats::model.matrix` `opsr_2step` *Heckman Two-Step Estimation*

Description

This is a utility function, used in `opsr` and should not be used directly. Tow-step estimation procedure to generate reasonable starting values.

Usage

```
opsr_2step(W, Xs, Z, Ys)
```

Arguments

`W`	matrix with explanatory variables for selection process.
`Xs`	list of matrices with expalanatory varialbes for outcome process for each regime.
`Z`	vector with ordinal outcomes (in integer increasing fashion).
`Ys`	list of vectors with continuous outcomes for each regime.

Details

These estimates can be retrieved by specifying `.get2step = TRUE` in `opsr`.

Value

Named vector with starting values passed to `opsr.fit`.

Remark

Since the Heckman two-step estimator includes an estimate in the second step regression, the resulting OLS standard errors and heteroskedasticity-robust standard errors are incorrect (Greene, 2002).

References

Greene WH (2002). *LIMDEP Version 8.0 Econometric Modeling Guide, vol. 2*. Econometric Software, Plainview, New York

See Also

`opsr.fit`, `opsr_prepare_coefs`

`opsr_check_omp`	*Check Whether `OpenMP` is Available*

Description

Check Whether `OpenMP` is Available

Usage

```
opsr_check_omp()
```

Value

boolean

`opsr_check_start`	*Check the User-Specified Starting Values*

Description

This is a utility function, used in `opsr` and should not be used directly. It is included here to document the expected structure of `opsr`'s `start` argument. Makes sure, the start vector conforms to the expected structure. Adds the expected parameter names to the numeric vector. Therefore the user has to conform to the expected order. See 'Details' for further explanation.

Usage

```
opsr_check_start(start, W, Xs)
```

Arguments

`start`	vector of starting values.
`W`	matrix with explanatory variables for selection process.
`Xs`	list of matrices with expalanatory varialbes for outcome process for each regime.

Details

Expected order: 1. kappa threshold parameters (for ordered probit model), 2. parameters of the selection process (names starting with `s_`), 3. parameters of the outcome processes (names starting with `o[0-9]_`), 4. sigma, 5. rho. If the same outcome process specification is used in the `formula`, the starting values have to be repeated (i.e., the length of the `start` vector has to correspond to the total number of estimated parameters in the model).

Value

Named numeric vector conforming to the expected structure.

See Also

`opsr_2step`

`opsr_max_threads` *Check Maximum Number of Threads Available*

Description

Check Maximum Number of Threads Available

Usage

```
opsr_max_threads()
```

Value

integer

See Also

`opsr_check_omp`

`opsr_null_model` *Null Model for OPSR Model fits*

Description

Intercept-only model with no error correlation.

Usage

```
opsr_null_model(object, ...)
```

Arguments

`object`	an object of class `"opsr"`.
`...`	further arguments passed to `opsr`.

Value

An object of class `"opsr.null" "opsr"`.

Examples

```
sim_dat <- opsr_simulate()
dat <- sim_dat$data
model <- ys | yo ~ xs1 + xs2 | xo1 + xo2
fit <- opsr(model, dat)
fit_null <- opsr_null_model(fit)
summary(fit_null)
```

`opsr_prepare_coefs` *Prepares Coefficients for Likelihood Function*

Description

Extracts the coefficients for each regime

Usage

```
opsr_prepare_coefs(theta, nReg)
```

Arguments

`theta`	named coefficient vector as parsed from formula interface `opsr`.
`nReg`	integer number of regimes.

Value

Named list of length `nReg`

Examples

```
sim_dat <- opsr_simulate()
dat <- sim_dat$data
model <- ys | yo ~ xs1 + xs2 | xo1 + xo2
start <- opsr(model, dat, .get2step = TRUE)
opsr_prepare_coefs(start, 3)
```

`opsr_simulate` *Simulate Data from an OPSR Process*

Description

Simulates data from an ordered probit process and separate (for each regime) OLS process where the errors follow a multivariate normal distribution.

Usage

```
opsr_simulate(nobs = 1000, sigma = NULL)
```

Arguments

`nobs`	number of observations to simulate.
`sigma`	the covariance matrix of the multivariate normal.

Details

Three ordinal outcomes are simulated and the distinct design matrices (`W` and `X`) are used (if `W == X` the model is poorly identified). Variables `ys` and `xs` in `data` correspond to the selection process and `yo`, `xo` to the outcome process.

Value

Named list:

`params`	ground truth parameters.
`data`	simulated data (as observed by the researcher). See also 'Details' section.
`errors`	error draws from the multivariate normal (as used in the latent process).
`sigma`	assumed covariance matrix (to generate `errors`).

`opsr.fit` *Fitter Function for Ordered Probit Switching Regression Models*

Description

This is the basic computing engine called by `opsr` used to fit ordinal probit switching regression models. Should usually *not* be used directly. The log-likelihood function is implemented in C++ which yields a considerable speed-up. Parallel computation is implemented using `OpenMP`.

Usage

```
opsr.fit(
  Ws,
  Xs,
  Ys,
  start,
  fixed,
  weights,
  method,
  iterlim,
  printLevel,
  nThreads,
  .useR = FALSE,
  .loglik = FALSE,
  ...
)
```

Arguments

`Ws`	list of matrices with explanatory variables for selection process for each regime.
`Xs`	list of matrices with expalanatory varialbes for outcome process for each regime.
`Ys`	list of vectors with continuous outcomes for each regime.
`start`	a numeric vector with the starting values (passed to `maxLik::maxLik`).
`fixed`	parameters to be treated as constants at their `start` values. If present, it is treated as an index vector of `start` parameters (passed to `maxLik::maxLik`).
`weights`	a vector of weights to be used in the fitting process. Has to conform with order (`w <- weights[order(Z)]`, where Z is the ordinal outcome).
`method`	maximzation method (passed to `maxLik::maxLik`).
`iterlim`	maximum number of iterations (passed to `maxLik::maxLik`).
`printLevel`	larger number prints more working information (passed to `maxLik::maxLik`).

`nThreads`	number of threads to be used. Do not pass higher number than number of ordinal outcomes. See also `opsr_check_omp` and `opsr_max_threads`.
`.useR`	if `TRUE`, usese `loglik_R`. Go grab a coffe.
`.loglik`	if `TRUE`, returns the vector of log-likelihood values given the parameters passed via `start`.
`...`	further arguments passed to `maxLik::maxLik`.

Value

object of class `"maxLik" "maxim"`.

See Also

`maxLik::maxLik`, `loglik_cpp`, `opsr`

`opsr` *Fitting Ordered Probit Switching Regression Models*

Description

High-level formula interface to the workhorse `opsr.fit`.

Usage

```
opsr(
  formula,
  data,
  subset,
  weights,
  na.action,
  start = NULL,
  fixed = NULL,
  method = "BFGS",
  iterlim = 1000,
  printLevel = 2,
  nThreads = 1,
```

```
    .get2step = FALSE,
    .useR = FALSE,
    .censorRho = TRUE,
    .loglik = FALSE,
    ...
)
```

Arguments

`formula`	an object of class `"Formula"` `"formula"`: A symbolic description of the model to be fitted. The details of model specification are given under 'Details'.
`data`	an optional data frame, list or environment (or object coercible by `as.data.frame` to a data frame) containing the variables in the model. If not found in `data`, the variables are taken from `environment(formula)`, typically the environment from which `opsr` is called.
`subset`	an optional vector specifying a subset of observations to be used in the fitting process. (See additional details in the 'Details' section of the `model.frame` documentation.).
`weights`	an optional vector of weights to be used in the fitting process. Should be `NULL` or a numeric vector. If non-NULL, then observation-specific log-likelihood contributions are multiplied by their corresponding weight before summing.
`na.action`	a function which indicates what should happen when the data contain `NA`s. The default is set by the `na.action` setting of `options`, and is `na.fail` if that is unset. The 'factory-fresh' default is `na.omit`. Another possible value is `NULL`, no action. Value `na.exclude` can be useful.
`start`	a numeric vector with the starting values (passed to `maxLik::maxLik`). If no starting values are provided, reasonable values are auto-generated via the Heckman 2-step procedure `opsr_2step`. The structure of `start` has to conform with `opsr`'s expectations. See `opsr_check_start` for further details.

`fixed`	parameters to be treated as constants at their `start` values. If present, it is treated as an index vector of `start` parameters (passed to `maxLik::maxLik`).
`method`	maximzation method (passed to `maxLik::maxLik`).
`iterlim`	maximum number of iterations (passed to `maxLik::maxLik`).
`printLevel`	larger number prints more working information (passed to `maxLik::maxLik`).
`nThreads`	number of threads to be used. Do not pass higher number than number of ordinal outcomes. See also `opsr_check_omp` and `opsr_max_threads`.
`.get2step`	if `TRUE`, returns starting values as generated by `opsr_2step`. Will not proceed with the maximum likelihood estimation.
`.useR`	if `TRUE` usese `loglik_R`. Go grab a coffe.
`.censorRho`	if `TRUE`, rho starting values are censored to lie in the interval [-0.85, 0.85].
`.loglik`	if `TRUE`, returns the vector of log-likelihood values given the parameters passed via `start`.
`...`	further arguments passed to `maxLik::maxLik`.

Details

Models for `opsr` are specified symbolically. A typical model has the form `ys | yo ~ terms_s | terms_o1 | terms_o2 | ...`. `ys` is the ordered (numeric) response vector (starting from 1, in integer-increasing fashion). For the `terms` specification the rules of the regular formula interface apply (see also `stats::lm`). The intercept in the `terms_s` (selection process) is excluded automatically (no need to specify `-1`). If the user wants to specify the same process for all continuous outcomes, two processes are enough (`ys | yo ~ terms_s | terms_o`). Note that the model is poorly identifiable if `terms_s == terms_o` (same regressors are used in selection and outcome processes).

Value

An object of class `"opsr" "maxLik" "maxim"`.

Examples

```
## simulated data
sim_dat <- opsr_simulate()
dat <- sim_dat$data  # 1000 observations
sim_dat$sigma  # cov matrix of errors
sim_dat$params  # ground truth

## specify a model
model <- ys | yo ~ xs1 + xs2 | xo1 + xo2 | xo1 + xo2 | xo1 + xo2
## since we use the same specification...
model <- ys | yo ~ xs1 + xs2 | xo1 + xo2

## estimate
fit <- opsr(model, dat)

## inference
summary(fit)

## using update and model comparison
## only intercepts for the continuous outcomes
fit_updated <- update(fit, ~ . | 1)
## null model
fit_null <- opsr_null_model(fit)

## likelihood ratio test
anova(fit_null, fit_updated, fit)

## predict
p1 <- predict(fit, group = 1, type = "response")
p2 <- predict(fit, group = 1, counterfact = 2, type = "response")
plot(p1, p2)
abline(a = 0, b = 1, col = "red")

## produce formatted tables
texreg::screenreg(fit, beside = TRUE, include.pseudoR2 = TRUE,
                  include.R2 = TRUE)
```

`predict.opsr` *Predict Method for OPSR Model Fits*

Description

Obtains predictions for the selection process (probabilities), the outcome process, or returns the inverse mills ratio. Handles also log-transformed outcomes.

Usage

```
## S3 method for class 'opsr'
predict(
  object,
  newdata,
  group,
  counterfact = NULL,
  type = c("response", "unlog-response", "prob", "mills",
           "correction", "Xb"),
  delta = 1,
  ...
)
```

Arguments

`object`	an object of class `"opsr"`.
`newdata`	an optional data frame in which to look for variables used in `object$formula`. See also `model.matrix.opsr`.
`group`	predict outcome of this group (regime).
`counterfact`	counterfactual group.
`type`	type of prediction. Can be abbreviated. See 'Details' section for more information.
`delta`	constant that was added during the continuity correction ($log(Y_j + \delta)$). Only applies for `type = "unlog-response"`.
`...`	further arguments passed to or from other methods.

Details

Elements are `NA_real_` if the `group` does not correspond to the observed regime (selection outcome). This ensures consistent output length.

If the `type` argument is `"response"` then the continuous outcome is predicted. Use `"unlog-response"` if the outcome response was log-transformed (i.e., either in the `formula` specification or during data pre-processing). `"prob"` returns the probability vector of belonging to `group`, `"mills"` returns the inverse mills ratio, `"correction"` the heckman correction (i.e., $\rho_j * \sigma_j *$ mills) and `"Xb"` returns $X\beta$.

Value

a vector of length `nrow(newdata)` (or data used during estimation).

See Also

`stats::predict`

Examples

```
sim_dat <- opsr_simulate()
dat <- sim_dat$data
model <- ys | yo ~ xs1 + xs2 | xo1 + xo2
fit <- opsr(model, dat)
p <- predict(fit, group = 1, type = "response")

fit_log <- update(fit, . | log(yo) ~ .)
p_unlog <- predict(fit, group = 1, type = "unlog-response")
```

`print.anova.opsr` *Print Method for ANOVA OPSR Objects*

Description

Print Method for ANOVA OPSR Objects

Usage

```
## S3 method for class 'anova.opsr'
print(
  x,
  digits = max(getOption("digits") - 2L, 3L),
  signif.stars = getOption("show.signif.stars"),
```

```
    print.formula = TRUE,
    ...
  )
```

Arguments

`x`	an object of class `"anova.opsr"`.
`digits`	minimal number of *significant* digits, see `print.default`.
`signif.stars`	if `TRUE`, P-values are additionally encoded visually as 'significance stars' in order to help scanning of long coefficient tables. It defaults to the `show.signif.stars` slot of `options`.
`print.formula`	if `TRUE`, the formulas of the models are printed.
`...`	further arguments passed to `stats::printCoefmat`.

Value

Prints tables in a 'pretty' form and returns `x` invisibly.

See Also

`stats::printCoefmat`, `anova.opsr`

`print.summary.opsr` *Print Method for Summary OPSR Objects*

Description

Print Method for Summary OPSR Objects

Usage

```
## S3 method for class 'summary.opsr'
print(x, digits = max(3L, getOption("digits") - 3L),
      print.call = TRUE, ...)
```

Arguments

`x`	and object of class `"summary.opsr"`
`digits`	minimum number of significant digits to be used for most numbers (passed to `stats::printCoefmat`).
`print.call`	if `TRUE`, prints the underlying `opsr` call.
`...`	further arguments passed to or from other methods.

Value

Prints summary in 'pretty' form and returns `x` invisibly.

See Also

`stats::printCoefmat`, `summary.opsr`

`summary.opsr` *Summarizing OPSR Model Fits*

Description

Follows the convention that `opsr` does the bare minimum model fitting and inference is performed in `summary`.

Usage

```
## S3 method for class 'opsr'
summary(object, rob = TRUE, ...)
```

Arguments

`object`	an object of class `"opsr"`.
`rob`	if `TRUE`, the `sandwich::sandwich` covariance matrix extimator is used.
`...`	further arguments passed to or from other methods.

Value

An object of class `"summary.opsr"`. In particular the elements `GOF`, `GOFcomponents` and `wald` require further explanation:

`GOF` Contains the conventional *goodness of fit* indicators for the full model. `LL2step` is the log-likelihood of the Heckman two-step solution (if the default starting values were used). `LLfinal` is the log-likelihood at final convergence and `AIC`, `BIC` the corresponding information critereon.

`GOFcomponents` Contains the *goodness of fit* for the model components. `LLprobit` is the log-likelihood (LL) contribution of the ordered probit model. `LLprobitEl` the LL of the "equally likely" and `LLprobitMs` the LL of the "market share" model. With these three metrics the pseudo R2 is computed and returned as `pseudoR2el` and `pseudoR2ms`. `R2` reports the usual coefficient of determination (for the continuous outcomes jointly and for each regime separately).

`wald` Contains the results of two *Wald-tests* as conducted with help of `car::linearHypothesis`. The two H0 hypothesis are 1. All coefficients of the explanatory variables are 0 and 2. The rho parameters (capturing error correlation) are zero.

`telework_data` *Telework Data*

Description

Telework data as used in Wang and Mokhtarian (2024).

Usage

```
telework_data
```

Format

Data frame with numeric columns

ID Respondent ID

WEIGHT Sample weight

VMD Weekly vehicle-miles traveled

VMD_LN Log-transformed VMD, the dependent variable of the outcome model

TWING_STATUS Teleworking status: 1=Non-TWer, 2=Non-usual TWer, 3=Usual TWer

FEMALE Sex: female

AGE_MEAN Mean-centered age

AGE_MEAN_SQ Sqaure of mean-centered age

RACE_WHITE Race: white only

RACE_BLACK Race: black only

RACE_OTHER Race: other

EDU_1 Education: high school or lower

EDU_2 Education: some college

EDU_3 Education: BA or higher

HHINCOME_1 Household income: less than $50,000

HHINCOME_2 Household income: $50,000 to $99,999

HHINCOME_3 Household income: $100,000 or more

FLEX_WORK Flexible work schedule

WORK_FULLTIME Full-time worker

TWING_FEASIBILITY Teleworking feasibility (days/month)

VEHICLE Number of household vehicles

CHILD Number of children

URBAN Residential location: urban

SUBURBAN Residential location: suburban

SMALLTOWN Residential location: small town

RURAL Residential location: rural

ATT_PROLARGEHOUSE Attitude: pro-large-house

ATT_PROACTIVEMODE Attitude: pro-active-mode

ATT_PROCAROWNING Attitude: pro-car-owning

ATT_WIF Attitude: work-interferes-with-family

ATT_PROTEAMWORK Attitude: pro-teamwork

ATT_TW_EFFECTIVE_TEAMWORK Attitude: TW effective teamwork

ATT_TW_ENTHUSIASM Attitude: TW enthusiasm

ATT_TW_LOCATION_FLEX Attitude: TW location flexibility

REGION_WAA Region indicator: respondents from WAA MSA

References

Wang X, Mokhtarian PL (2024). "Examining the Treatment Effect of Teleworking on Vehicle-Miles Driven: Applying an Ordered Probit Selection Model and Incorporating the Role of Travel Stress." *Transportation Research Part A*, **186**, 104072. doi:10.1016/j.tra.2024.104072

Examples

```
## model as in Xinyi & Mokhtarian (2024)
f <-
  ## ordinal and continuous outcome
  twing_status | vmd_ln ~
  ## selection model
  edu_2 + edu_3 + hhincome_2 + hhincome_3 +
  flex_work + work_fulltime + twing_feasibility +
  att_proactivemode + att_procarowning +
  att_wif + att_proteamwork +
  att_tw_effective_teamwork + att_tw_enthusiasm + att_tw_location_flex |
  ## outcome model NTW
  female + age_mean + age_mean_sq +
  race_black + race_other +
  vehicle + suburban + smalltown + rural +
  work_fulltime +
  att_prolargehouse + att_procarowning +
  region_waa |
  ## outcome model NUTW
  edu_2 + edu_3 + suburban + smalltown + rural +
  work_fulltime +
  att_prolargehouse + att_proactivemode + att_procarowning |
```

```
  ## outcome model UTW
  female + hhincome_2 + hhincome_3 +
  child + suburban + smalltown + rural +
  att_procarowning +
  region_waa

fit <- opsr(f, telework_data)
texreg::screenreg(fit, beside = TRUE, include.pseudoR2 = TRUE,
                  include.R2 = TRUE)
```

`timeuse_data` *TimeUse+ Data*

Description

TimeUse+ (Winkler *et al.*, 2024) was a tracking study conducted at the Institute for Transport Planning and Systems (IVT) at ETH Zurich. The data allows researchers to investigate time-use and mobility patterns. Full data access can be requested via doi:10.3929/ethz-b-000634868.

Usage

```
timeuse_data
```

Format

Data frame with numeric and factor columns

ID Respondent ID

START_TRACKING Indicator for the months when the participant started tracking

WEEKLY_KM Weekly distance covered (in km) across all modes

LOG_WEEKLY_KM Log of `weekly_km`

WFH_DAYS Based on tracked work episodes. Average full working days spent in home office during a typical week.

WFH Derived from `wfh_days`: NTW=Non-TWer, NUTW=Non-usual TWer (< 3 days/week), UTW=Usual TWer(3+ days/week)

COMMUTE_KM Map matched commute distance in km

LOG_COMMUTE_KM Log of `commute_km`

AGE Age

CAR_ACCESS Has access to a household car

DOGS Household owns dogs

DRIVERLICENSE Owns driver's license for cars

EDUC_HIGHER Higher education (e.g., university)

FIXED_WORKPLACE Main work location does not change regularly

GROCERY_SHOPPER Does usually do the grocery shopping

HH_INCOME Gross household income per month (CHF)

HH_SIZE Total household size

ISCO_CLERICAL International standard classification of Occupations (ISCO-08): Clerical support workers

ISCO_CRAFT International standard classification of Occupations (ISCO-08): Craft related trade workers

ISCO_ELEMENTARY International standard classification of Occupations (ISCO-08): Elementary occupations

ISCO_MANAGERS International standard classification of Occupations (ISCO-08): Managers

ISCO_PLANT International standard classification of Occupations (ISCO-08): Plant and machine operators, and assemblers

ISCO_PROFESSIONALS International standard classification of Occupations (ISCO-08): Professionals

ISCO_SERVICE International standard classification of Occupations (ISCO-08): Service and sales workers

ISCO_AGRI International standard classification of Occupations (ISCO-08): Skilled agricultural, forestry and fishery workers

ISCO_TECH International standard classification of Occupations (ISCO-08): Technicians and associate professionals

MARRIED Married

N_CHILDREN Number of household members below the age of 18

FREQ_ONL_ORDER Orders products online more than once a month

PARKING_HOME Has at least one reserved parking space at home

PARKING_WORK Has at least one reserved parking space at work location

PERMANENT_EMPLOYMENT Employment contract type: permenent (unlimited employed)

RENTS_HOME Residential situation: Rents home

RES_LOC Residential location

SEX_MALE Gender

SHIFT_WORK Whether participant works in shifts

SWISS Swiss citizen

VACATION Participant took time off of work during study

WORKLOAD Workload (% of full-time employment which is 41.7 h/week)

YOUNG_KIDS Whether children aged 12 or younger live in the household

Details

The data comprises employed individuals only and is based on valid days only. A valid day has at least 20h of information where 70% of the events were validated by the user. The telework variables are based on tracked work activities.

References

Winkler C, Meister A, Axhausen KW (2024). "The TimeUse+ Data Set: 4 Weeks of Time Use and Expenditure Data Based on GPS Tracks." *Transportation*, pp. 1–27. doi:10.1007/s11116-024-10517-1

A.3.2 **OPSRtools** *reference manual*

`OPSRtools-package` *OPSRtools: Tools for OPSR*

Description

OPSR estimates ordered probit switching regression models - a Heckman type endogenous switching regression model with an ordinal selection/treatment and continuous outcomes. OPSRtools contains estimation and post-estimation routines such as step-wise model selection, k-fold cross-validation, treatment effect computations and some visualizations.

Author(s)

Maintainer: Daniel Heimgartner `<d.heimgartners@gmail.com>` (ORCID) [copyright holder]

`kfplot` *Comparison Plot Method for List of OPSR kfold Objects*

Description

Comparison Plot Method for List of OPSR kfold Objects

Usage

```
kfplot(
  x,
  i = c("ll_mean", "ll_p_mean", "r2"),
  main = NULL,
  xlab = NULL,
  ylab = NULL,
  ...
)
```

Arguments

`x`	a list of objects of class `"opsr.kfold"`.
`i`	the loss to extract (see 'Value' in `loss`). One of `"ll_mean"`, `"ll_p_mean"` or `"r2"`.
`main`	a main title for the plot, see also `title`.
`xlab`	a label for the x axis.
`ylab`	a label for the y axis.
`...`	further arguments passed to `boxplot`.

Value

See 'Value' in `boxplot`.

See Also

`loss`

`list2df` *List to Data Frame*

Description

Converts a list of vectors to a data frame.

Usage

```
list2df(x)
```

Arguments

`x`	a list of vectors.

Value

A data frame.

`loss` *Out-Of-Sample Goodness of Fit Indicators*

Description

Computes a loss for out-of-sample data points.

Usage

```
loss(object, data, test_ind, ...)
```

Arguments

`object`	an object of class `"opsr"`.
`data`	a data frame containing the variables in the model (usually from a call to `model.frame.opsr`).
`test_ind`	indicator for the test data.
`...`	addditional arguments passed to `opsr_from_opsr`.

Value

A list containing the losses:

- `z`: The regime/treatment membership of the test data.
- `ll`: The out-of-sample log-likelihood of the test data.
- `ll_mean`: `ll` averaged over each regime and in total.
- `ll_p`: The out-of-sample log-likelihood of the test data for the selection process.
- `ll_p_mean`: `ll_p` averaged over each regime and in total.
- `r2`: Coefficient of determination for each regime and in total.

`opsr_ate`	*Treatment Effect Computations for OPSR Model Fits*

Description

Treatment Effect Computations for OPSR Model Fits

Usage

```
opsr_ate(object, type, weights = NULL, ...)
```

Arguments

`object`	object an object of class `"opsr"`.
`type`	see `predict.opsr` for details.
`weights`	a vector of weights. If `NULL` then weights from `object` will be used.
`...`	additional arguments passed to `predict.opsr`.

Details

This function only prepares the input to a further call to `summary.opsr.ate`.

Value

An object of class `"opsr.ate"`.

See Also

`summary.opsr.ate`

Examples

```
sim_dat <- OPSR::opsr_simulate()
dat <- sim_dat$data
weights <- runif(nrow(dat))
fit <- OPSR::opsr(ys | yo ~ xs1 + xs2 | xo1 + xo2, dat = dat,
                  weights = weights, printLevel = 0)
```

```
ate <- opsr_ate(fit, type = "response")
print(ate)
summary(ate)

ate_w <- opsr_ate(fit, type = "response", weights = rep(1, nrow(dat)))
summary(ate_w)

pairs(ate)
```

`opsr_from_opsr` *Refit an OPSR Model on New Data*

Description

Refit an OPSR Model on New Data

Usage

```
opsr_from_opsr(object, data, ...)
```

Arguments

`object`	an object of class `"opsr"`.
`data`	a data frame containing the variables in the model.
`...`	additional arguments passed to `opsr`.

Value

An object of class `"opsr"`

`opsr_kfold` *k-Fold Cross-Validation for OPSR Model Fits*

Description

Computes out-of-sample losses.

Usage

```
opsr_kfold(object, k = 10, verbose = TRUE, ...)
```

Arguments

`object`	an object of class `"opsr"`.
`k`	number of folds.
`verbose`	if `TRUE`, prints working information during iterations over folds.
`...`	additional arguments passed to `opsr_from_opsr`

Details

The returned object is of length `k`, where each element contains the losses as computed by `loss`.

Value

An object of class `"opsr.kfold"`. See 'Details' section for more information.

See Also

`opsr_from_opsr`, `loss`, `[.opsr.kfold`

Examples

```
sim_dat <- OPSR::opsr_simulate()
dat <- sim_dat$data
dat$xo3 <- runif(n = nrow(dat))
dat$xo4 <- factor(sample(c("level1", "leve2", "level3"), nrow(dat),
```

```
                    replace = TRUE))
f <- ys | yo ~ xs1 + xs2 + log(xo3) | xo1 + xo2 + xo3 + xo4 |
  xo1 + xo2 + xo3 | xo1 + xo2
fit <- OPSR::opsr(f, dat, printLevel = 0)
fit_select <- opsr_select(fit, loss = "bic", printLevel = 0)
kfold <- opsr_kfold(fit, printLevel = 0)
kfold_select <- opsr_kfold(fit_select, printLevel = 0)

## extract
ll_mean <- kfold["ll_mean"]
list2df(ll_mean)

## plot
colvec <- c("#ff8811","#48a9a6")
kfplot(list(kfold, kfold_select), col = colvec)
legend("bottomleft", legend = c("fit", "fit_select"), fill = colvec,
       title = "Model", title.font = 2, bty = "n")
```

`opsr_select`	*Select a Model in a Stepwise Algorithm*

Description

Iteratively calls `opsr_step` and compares the resulting model to the current winner (as evaluated by a selected loss function).

Usage

```
opsr_select(
  object,
  pseq = seq(0.9, 0.1, by = -0.1),
  log = new.env(),
  verbose = TRUE,
  loss = c("aic", "bic", "lrt"),
  ...
)
```

Arguments

`object`	an object of class `"opsr"`.

`pseq`	sequence of p-value thresholds (each of which is passed as `pval` to `opsr_step`).
`log`	environment to keep track of changes to `object` (in particular variables being eliminated).
`verbose`	if `TRUE`, prints working information during computation.
`loss`	The loss function for model comparison. Can be abbreviated. See 'Details' section for more information.
`...`	additional arguments passed to `opsr_select`

Details

Currently three loss functions are available which can be selected via the `loss` argument. The loss is then computed for the two models to be compared and a winner is selected. Can be one of `"aic"` for AIC, `"bic"` for BIC and `"lrt"` for a likelihood ratio test.

Value

An object of class `"opsr.select"`.

See Also

`opsr_select`

Examples

```
sim_dat <- OPSR::opsr_simulate()
dat <- sim_dat$data
dat$xo3 <- runif(n = nrow(dat))
dat$xo4 <- factor(sample(c("level1", "leve2", "level3"), nrow(dat),
                  replace = TRUE))
f <- ys | yo ~ xs1 + xs2 + log(xo3) | xo1 + xo2 + xo3 + xo4 |
  xo1 + xo2 + xo3 | xo1 + xo2
fit <- OPSR::opsr(f, dat, printLevel = 0)
fit_select <- opsr_select(fit, loss = "aic", printLevel = 0)
print(fit_select)
```

`opsr_step` *Step Function for OPSR Model Fits*

Description

Excludes all coefficients with p-values below `pval` and fits again.

Usage

```
opsr_step(object, pval, log = new.env(), .step = 1, ...)
```

Arguments

`object`	an object of class `"opsr"`.
`pval`	coefficients with p-values < `pval` are dropped.
`log`	environment to keep track of changes to `object` (in particular variables being eliminated).
`.step`	used to generate identifier in `log` environment. Used in `opsr_select`.
`...`	additional arguments passed to `update` (and hence `opsr`).

Value

An object of class `"opsr"`.

See Also

`opsr_select`

Examples

```
sim_dat <- OPSR::opsr_simulate()
dat <- sim_dat$data
dat$xo3 <- runif(n = nrow(dat))
dat$xo4 <- factor(sample(c("level1", "leve2", "level3"), nrow(dat),
                  replace = TRUE))
f <- ys | yo ~ xs1 + xs2 + log(xo3) | xo1 + xo2 + xo3 + xo4 |
```

```
  xo1 + xo2 + xo3 | xo1 + xo2
fit <- OPSR::opsr(f, dat, printLevel = 0)
fit_step <- opsr_step(fit, pval = 0.1)
texreg::screenreg(list(fit, fit_step))
```

pairs.opsr.ate *Pairs Plot for OPSR ATE Objects*

Description

Pairs Plot for OPSR ATE Objects

Usage

```
## S3 method for class 'opsr.ate'
pairs(
  x,
  pch = 21,
  labels.diag = paste0("T", 1:x$nReg),
  labels.reg = paste0("G", 1:x$nReg),
  col = 1:x$nReg,
  add.rug = TRUE,
  lower.digits = 0,
  diag.digits = 0,
  lwd.dens = 1.5,
  diag.cex.text = 1,
  upper.digits = 2,
  upper.cex.text = 2,
  prefix = "",
  postfix = "",
  lty.diag = 1,
  ...
)
```

Arguments

`x`	an object of class `"opsr.ate"`.
`pch`	plotting 'character', i.e., symbol to use. See also `pch`.

`labels.diag`	labels used in the diagonal panels.
`labels.reg`	labels for the treatment regimes.
`col`	colour vector.
`add.rug`	if `TRUE`, adds rugs to the lower panels.
`lower.digits`	rounding of the digits in the lower panel.
`diag.digits`	rounding of the digits in the diagonal panel.
`lwd.dens`	linewidth of the densities in the diagonal panel.
`diag.cex.text`	`cex` for the text in the diagonal panel.
`upper.digits`	rounding of the digits in the upper panel.
`upper.cex.text`	`cex` for the text in the upper panel.
`prefix`	for the number plotted in the upper panel.
`postfix`	for the number plotted in the upper panel.
`lty.diag`	linetype for the diagonal panel.
`...`	further arguments passed to or from other methods.

Details

Presents all potential counterfactual outcomes. The diagonal depicts distributions in any given treatment regime and separate by the current (factual) treatment group. The weighted mean values are shown as red numbers. The lower triangular panels compare the model-implied (predicted) outcomes of two treatment regimes again separate by current treatment group. The red line indicates the 45-degree line of equal outcomes while the red squares depict again the weighted mean values. The upper triangular panels show (weighted) average treatment effects.

Value

Returns `x` invisibly.

See Also

`pairs`

Examples

```
sim_dat <- OPSR::opsr_simulate()
dat <- sim_dat$data
weights <- runif(nrow(dat))
fit <- OPSR::opsr(ys | yo ~ xs1 + xs2 | xo1 + xo2, dat = dat,
                  weights = weights, printLevel = 0)
ate <- opsr_ate(fit, type = "response")
print(ate)
summary(ate)

ate_w <- opsr_ate(fit, type = "response", weights = rep(1, nrow(dat)))
summary(ate_w)

pairs(ate)
```

`plot.opsr.kfold` *Plot Method for OPSR kfold Objects*

Description

Plot Method for OPSR kfold Objects

Usage

```
## S3 method for class 'opsr.kfold'
plot(
  x,
  i = c("ll_mean", "ll_p_mean", "r2"),
  main = NULL,
  xlab = NULL,
  ylab = NULL,
  ...
)
```

Arguments

`x`	an object of class `"opsr.kfold"`.
`i`	the loss to extract (see 'Value' in `loss`). One of `"ll_mean"`, `"ll_p_mean"` or `"r2"`.

`main`	a main title for the plot, see also `title`.
`xlab`	a label for the x axis.
`ylab`	a label for the y axis.
`...`	further arguments passed to `boxplot`.

Value

See 'Value' in `boxplot`.

See Also

`loss`

`print.ate` *Print Method for ATE Objects*

Description

Print Method for ATE Objects

Usage

```
## S3 method for class 'ate'
print(x, digits = max(3L, getOption("digits") - 3L),
      signif.legend = TRUE, ...)
```

Arguments

`x`	an object of class `"ate"`.
`digits`	minimum number of significant digits to be used for most numbers (passed to `stats::printCoefmat`).
`signif.legend`	if `TRUE`, a legend for the 'significance stars' is printed.
`...`	further arguments passed to or from other methods.

Value

Prints `x` in 'pretty' form and returns reformatted treatment effects invisibly.

`print.opsr.ate` *Print Method for OPSR ATE Objects*

Description

Print Method for OPSR ATE Objects

Usage

```
## S3 method for class 'opsr.ate'
print(x, ...)
```

Arguments

`x`	an object of class `"opsr.ate"`.
`...`	further arguments passed to `summary.opsr.ate`.

Details

This is just a wrapper around `summary.opsr.ate` and a subsequent call to `print.summary.opsr.ate`.

Value

Returns `x` invisibly.

See Also

`print.summary.opsr.ate`

`print.opsr.select` *Print Method for OPSR Select Objects*

Description

Prints the original model and the final model (winner) as well as the stepwise model path.

Usage

```
## S3 method for class 'opsr.select'
print(
  x,
  digits = max(3L, getOption("digits") - 3L),
  print.call = TRUE,
  print.elim.hist = TRUE,
  ...
)
```

Arguments

`x`	an object of class `"opsr.select"`.
`digits`	minimum number of significant digits to be used for most numbers (passed to `stats::printCoefmat`).
`print.call`	if `TRUE`, prints the underlying `opsr_select` call.
`print.elim.hist`	if `TRUE`, prints the elimination history. See 'Details' section for more information.
`...`	further arguments passed to or from other methods.

Value

Prints `x` in 'pretty' form and returns it invisibly.

`print.summary.opsr.ate` *Print Method for Summary OPSR ATE Objects*

Description

Print Method for Summary OPSR ATE Objects

Usage

```
## S3 method for class 'summary.opsr.ate'
print(x, digits = max(3L, getOption("digits") - 3L),
      print.call = FALSE, ...)
```

Arguments

`x`	an object of class `"summary.opsr.ate"`.
`digits`	minimum number of significant digits to be used for most numbers (passed to `stats::printCoefmat`).
`print.call`	if `TRUE`, prints the underlying call.
`...`	further arguments passed to or from other methods.

Value

Prints `x` in 'pretty' form and returns it invisibly.

`print.te` *Print Method for TE Objects*

Description

Print Method for TE Objects

Usage

```
## S3 method for class 'te'
print(x, digits = max(3L, getOption("digits") - 3L),
      signif.legend = TRUE, ...)
```

Arguments

`x`	an object of class `"te"`.
`digits`	minimum number of significant digits to be used for most numbers (passed to `stats::printCoefmat`).
`signif.legend`	if `TRUE`, a legend for the 'significance stars' is printed.
`...`	further arguments passed to or from other methods.

Value

Prints `x` in 'pretty' form and returns reformatted treatment effects invisibly.

`[.opsr.kfold` *Extract Method for OPSR kfold Object*

Description

Extract Method for OPSR kfold Object

Usage

```
## S3 method for class 'opsr.kfold'
x[i]
```

Arguments

`x`	an object of class `"opsr.kfold"`.
`i`	the loss to extract (see 'Value' in `loss`).

Value

A list of length k (where k is the number of folds).

See Also

`loss`

`summary.opsr.ate` *Summarizing OPSR ATE Objects*

Description

This function computes weighted treatment effects and corresponding weighted paired t-tests.

Usage

```
## S3 method for class 'opsr.ate'
summary(object, ...)
```

Arguments

`object`	an object of class `"opsr.ate"`.
`...`	further arguments passed to or from other methods.

Value

An object of class `"summary.opsr.ate"` containing among others:

- `ate`: An object of class `"ate"`. See also `print.ate`.
- `te`: An object of class `"te"`. See also `print.te`.

The p-values of the weighted paired t-test are attached as attributes.

`timeuse` *TimeUse+ Data*

Description

Travel diary data from the TimeUse+ study (Winkler *et al.*, 2024).

Usage

```
timeuse
```

Format

Data frame with numeric and factor columns

UID Respondent ID

WEIGHT Sample weight

WFH Telework status

WFH_DAYS Telework frequency (days/week)

WEEKLY_KM Weekly kilometers traveled

LOG_WEEKLY_KM Log weekly kilometers traveled

WEEKLY_N Weekly number of trips

LOG_WEEKLY_N Log weekly number of trips

START_TRACKING Month when tracking started

COMMUTE One-way commute distance (km)

LOG_COMMUTE_KM Log one-way commute distance

AGE Age

CAR_ACCESS Car access

DOGS Has dogs

DRIVERLICENSE Has driverlicense

EDUC_HIGHER Higher education

FIXED_WORKPLACE Has fixed workplace

GROCERY_SHOPPER Main responsible for grocery shopping

HH_INCOME Household income

HH_SIZE Household size

ISCO_CLERICAL ISCO clerical

ISCO_CRAFT ISCO craft

ISCO_ELEMENTARY ISCO elementary

ISCO_MANAGERS ISCO managers

ISCO_PLANT ISCO plant and machine

ISCO_PROFESSIONALS ISCO professionals

ISCO_SERVICE ISCO service and sales

ISCO_AGRI ISCO agriculture

ISCO_TECH ISCO technicians

MARRIED Married

N_CHILDREN Number of children

FREQ_ONL_ORDER Frequent online shopper

PARKING_HOME Parking available at home

PARKING_WORK Parking available at work

PERMANENT_EMPLOYED Permanent employment

RENTS_HOME Tenant

RES_LOC Residential location

SEX_MALE Male

SHIFT_WORK Works in shifts

SWISS Nationality Swiss

VACATION Vacation during study

WORKLOAD Workload (in % of full-time equivalent)

YOUNG_KIDS Has young kids

WFH_ALLOWED Employer allows telework

TELEWORKABILITY Number of days worked from home during COVID-related lockdowns

References

Winkler C, Meister A, Axhausen KW (2024). "The TimeUse+ Data Set: 4 Weeks of Time Use and Expenditure Data Based on GPS Tracks." *Transportation*, pp. 1–27. doi:10.1007/s11116-024-10517-1

A.3.3 **snndata** *reference manual*

`snndata-package` *snndata: Data for the Swiss New Normal*

Description

Contains data collected for the project Multimodality in the Swiss New Normal. It allows researchers to investigate telework behavior in Switzerland, understand the importance of work arrangements on telework supply and the relation between telework and mobility tool ownership. The data collection methods are detailed in Heimgartner and Axhausen (2024b).

Author(s)

Maintainer: Daniel Heimgartner `<d.heimgartners@gmail.com>` (ORCID) [copyright holder]

Authors:

- Kay W. Axhausen `<axhausen@ivt.baug.ethz.ch>` (ORCID)

`features` *Some Additional Features*

Description

Typology and degree of urbanization for home and work location as well as commute distance.

Usage

```
features
```

Format

Data frame

UID Unique identifier for respondents

RE_ZIP Zip code of the municipality where the participant lives

WK_ZIP Zip code of the municipality where the participant works

COMMUTE_KM Crow fly distance from home to work

LOG_COMMUTE_KM Log transformed crow fly distance from home to work

RE_TYPOLOGY Typology of municipality where the participant lives

RE_URBANIZATION Degree of urbanization of municiplaity where the participant lives

WK_TYPOLOGY Typology of municiplaity where the participant works

WK_URBANIZATION Degree of urbanization of municiplaity where the participant works

See Also

`https://www.agvchapp.bfs.admin.ch/de/typologies/query`, `https://www.agvchapp.bfs.admin.ch/de/typologies/query`

`labels` *Variable Labels*

Description

Contains key value pairs mapping the raw recorded (Qualtrics) answer to a more user friendly one.

Usage

```
labels
```

Format

List of lists:

- `intro`: Labels for the variabels in survey_intro$main.
- `wfh`: Labels for the variables in survey_wfh$sp.
- `mto`: Labels for the variables in survey_mto$sp.
- `srph`: Labels for the variabels in srph.
- `mzmv`: Labels for the Microcencus Mobility and Transport (not part of `snndata`)

Details

The labels were used to recode the raw data as pulled from Qualtrics. The below mentioned data frames are slightly restructured and therefore, some of the variables contained there do not have a matching element in `labels`. Nevertheless, it can be useful to quickly consult the labels list in case you are not sure, what the abbreviation implies.

To work with the `labels` you might want to consider the **Heimisc** (Heimgartner, 2024a) or **labelr** (Good, 2024) package.

References

Heimgartner D (2024a). **Heimisc**: *Heimgartner Miscellaneous*. R package version 0.1.0, URL `https://github.com/dheimgartner/Heimisc` Good T (2024). **labelr**: *Label Your Data Frames*. R package version 0.0.2.9000, URL `https://github.com/ivt-baug-ethz/labelr`

Examples

```
unique(survey_intro$main$wk_status_1)
labels$intro$wk_status_1
```

`srph`	*Data from the Stichprobenrahmen (FSO)*

Description

We received the addresses from the Stichprobenrahmen (Federal Statistical Office, FSO). Along the addresses some socio-demographic information is contained in the data frame.

Usage

```
srph
```

Format

Data frame

UID Unique identifier for respondents

AGE Age

YEAROFBIRTH Year of birth

COUNTRYIDOFBIRTH Country where the respondent was born

SEX Gender

MARITALSTATUS Marital status

NATIONALITYSTATE Nationality (CHE, other or staatenlos)

REPORTINGMUNICIPALITYID Municipality where the respondent lives

REPORTINGCANTON Canton where the respondent lives

RESIDENCESWISSZIPCODE Zip code of municipality where the respondent lives

RESIDENCETOWN Town where the respondent lives

COMMUNICATIONLANGUAGE Language spoken at communal level

HOUSEHOLDSIZESRPH Household size

See Also

labels

`survey_id` *Survey Id*

Description

Qualtrics survey ids.

Usage

```
survey_id
```

Format

Named list

`survey_intro` *Introductory Survey*

Description

Basic background information on the respondents.

Usage

```
survey_intro
```

Format

List of data frames:

- `main`: Main variables of interest for the analysis (see section 'Main data frame').
- `timer`: How much time the respondents took to answer.
- `meta`: Some meta information as automatically collected by Qualtrics.
- `telework`: Main telework access and frequency variables (see section 'telework data frame').

Details

A representative sample of the German-speaking part of Switzerland was recruited. The final survey population encompasses individuals in the workforce (excluding self-employed, students and retired).

At survey launch there was a subtle bug in the survey logic where some of the telework related questions were asked to respondents without the option to telework. This led to confusion and random answers. We corrected for this mistake and the values reported in the `telework` data frame are reliable.

Main data frame

The `main` data frame contains:

- Socio-economic information
- Household structure
- Current telework status
- Telework status during and before the pandemic
- Work and residential situation
- Mobility behavior
- Mobility tool ownership

The labels are currently set to `filter == short`.

The BFI indicators (for personality traits) are based on Gerlitz and Schupp (2005).

UID Unique identifier for respondents

IS_SELF_EMPLOYED Self-employed

IS_IN_WORKFORCE In workforce

CONSENT Consented to participate

WK_STATUS_1 Employment status: employed

WK_STATUS_2 Employment status: self-employed

WK_STATUS_3 Employment status: unemployed

WK_STATUS_4 Employment status: apprentice

WK_STATUS_5 Employment status: student

WK_STATUS_6 Employment status: retired

wk_status_7 Employment status: other

wfh_fully_shift Could you shift `telework$feasible` days to home office without feeling pressured to return to the regular work place more often?

wfh_employer_pov How does your employer feel about home office

p_marital_status Marital status

p_education Highest completed level of education

hh_size_1 Household size: Young children (<6 years)

hh_size_2 Household size: Children (6-12 years)

hh_size_3 Household size: Children (13-18 years)

hh_size_4 Household size: Adults

hh_income Monthly household income: Annual income before taxes divided by 12

p_income Monthly personal income: Annual income before taxes divided by 12

re_type Residence type

re_size_1 Residence size: Number of rooms

re_size_2 Residence size: Square meters

re_nk What are the monthly additional costs (e.g., heating and hot water, house maintenance, waste water charges, costs for general electricity, etc.) of your residence?

re_second_1 Participant or household member has second residence, apartment or room within Switzerland

re_second_2 Participant or household member has second residence, apartment or room outside Switzerland

wk_full_time Works full time (100%)

wk_workload Workload (percentage of full-time employment)

wk_multiworkload_1 Percentage of full-time employment of main job (if participant works multiple jobs)

wk_multiworkload_2 Percentage of full-time employment of secondary job (if participant works multiple jobs)

wk_noga General classification of economic activities (NOGA 2008)

WK_FIRM_SIZE Firm size (number of employed)

WK_ISCO_CAT_1 International standard classification of Occupations (ISCO-08): Managers

WK_ISCO_CAT_2 International standard classification of Occupations (ISCO-08): Professionals

WK_ISCO_CAT_3 International standard classification of Occupations (ISCO-08): Technicians and associate professionals

WK_ISCO_CAT_4 International standard classification of Occupations (ISCO-08): Clerical support workers

WK_ISCO_CAT_5 International standard classification of Occupations (ISCO-08): Service and sales workers

WK_ISCO_CAT_6 International standard classification of Occupations (ISCO-08): Skilled agricultural, forestry and fishery workers

WK_ISCO_CAT_7 International standard classification of Occupations (ISCO-08): Craft related trade workers

WK_ISCO_CAT_8 International standard classification of Occupations (ISCO-08): Plant and machine operators, and assemblers

WK_ISCO_CAT_9 International standard classification of Occupations (ISCO-08): Elementary occupations

WK_ISCO_CAT_10 International standard classification of Occupations (ISCO-08): Armed forces occupations

WK_ISCO_CAT_TEXT International standard classification of Occupations (ISCO-08): Self-classification

WK_CONTRACT Type of employment contract

WK_CONTRACT_TEXT Type of employment contract: Other (please specify)

WK_SHIFTWORK Works in shifts

WK_SCHEDULE Work schedule

WK_SCHEDULE_TEXT Work schedule: Other (please specify)

WK_LEADER Manages or leads people (colinear with `wk_isco_cat_1`)

MO_DRIVING_LICENSE Has driving license for passenger cars (category B)

MO_MOTO_LICENSE Has driving license for motorcycles (category A/A1/A-)

MO_BIKESHARING_SUB Has bikesharing subscription

MO_MTO_PRE_COVID_1 Mobility tool ownership before the pandemic: Car

MO_MTO_PRE_COVID_2 Mobility tool ownership before the pandemic: Car sharing subscription

MO_MTO_PRE_COVID_3 Mobility tool ownership before the pandemic: Regular bike

MO_MTO_PRE_COVID_4 Mobility tool ownership before the pandemic: E-bike

MO_MTO_PRE_COVID_5 Mobility tool ownership before the pandemic: Motorbike

MO_MTO_PRE_COVID_6 Mobility tool ownership before the pandemic: National season ticket (GA)

MO_MTO_PRE_COVID_7 Mobility tool ownership before the pandemic: Regional season ticket

MO_MTO_PRE_COVID_8 Mobility tool ownership before the pandemic: Half-fare card (HT)

MO_MTO_NOW_1 Mobility tool ownership at survey date: Car

MO_MTO_NOW_2 Mobility tool ownership at survey date: Car sharing subscription

MO_MTO_NOW_3 Mobility tool ownership at survey date: Regular bike

MO_MTO_NOW_4 Mobility tool ownership at survey date: E-bike

MO_MTO_NOW_5 Mobility tool ownership at survey date: Motorbike

MO_MTO_NOW_6 Mobility tool ownership at survey date: National season ticket (GA)

MO_MTO_NOW_7 Mobility tool ownership at survey date: Regional season ticket

MO_MTO_NOW_8 Mobility tool ownership at survey date: Half-fare card (HT)

MO_MOTO_EVERYDAY Uses motorbike as daily means of transportation

MO_CAR_SIZE Car size

MO_CAR_FUEL Car fuel type

MO_CAR_VAR_COST Car's per kilometer cost considering all costs associated with car travel, including depreciation of the car's value, fuel or energy costs, tire costs and maintenance

MO_CAR_FIX_COST Annual fixed cost of the car including amortization, garaging costs, insurance as well as taxes and interest payments (if leased)

MO_PARKING_1 Reserved parking available at home

MO_PARKING_2 Reserved parking available at work

MO_PARKING_HOOD Available parking in the residential neighborhood

MO_COMPANY_CAR Employer offers a company car

MO_EBIKE_TYPE_1 Owns E-bike/pedelec up to 25 km/h (no license plate)

MO_EBIKE_TYPE_2 Owns E-bike/S-pedelect up to 45 km/h (yellow license plate)

MO_PT_PASS_1 Owns public transport pass: National season ticket (GA)

MO_PT_PASS_2 Owns public transport pass: Half-fare card (HT)

MO_PT_PASS_3 Owns public transport pass: Regional season ticket

MO_PT_PASS_4 Owns public transport pass: Seven25

MO_PT_PASS_5 Does not own any public transport pass

MO_PT_PASS_TEXT Owns public transport pass: Other (please specify)

MO_PT_CLASS Class eligibility of public transport pass (1st or 2nd)

MO_COMMUTE_MODE Main mode of transportation for commute

WK_BEFORE_PANDEMIC Participant worked before the pandemic

WK_SWITCH_BEFORE Participant switched job since the outbreak of the pandemic

WK_DURING_PANDEMIC Participant worked during the pandemic

WK_SWITCH_DURING Participant switched job since the end of the pandmic

WFH_HW_BUDGET Yearly budget required to set up a productive home office workstation

WFH_BUDGET_CONTRIB Employer's contribution to `wfh_hw_budget`

WFH_DESK_SHARING Desk sharing policy at workplace

WFH_WHICH_DAYS_1 Teleworking day: Monday

WFH_WHICH_DAYS_2 Teleworking day: Tuesday

WFH_WHICH_DAYS_3 Teleworking day: Wednesday

WFH_WHICH_DAYS_4 Teleworking day: Thursday

WFH_WHICH_DAYS_5 Teleworking day: Friday

WFH_WHICH_DAYS_6 Teleworking day: Saturday

WFH_WHICH_DAYS_7 Teleworking day: Sunday

WFH_COORDINATION Whether or not the teleworking days can be freely chosen

WFH_CORE_HOURS Whether or not the respondent is required to be available during particular hours when working from home

WFH_NK Whether or not the employer contributes to additional costs (e.g., heating and electricity costs) when employee works from home

WFH_SALARY_ADJUST Is the salary adjusted when working from home

WFH_WORK_FROM_ANY Work from anywhere policy or only designated home office location

WFH_HELP_AND_TRAIN Employer provides help desk for technical assistance or offers training for effective home office collaboration

RE_WFH_EQUIPMENT_1 Work from home equipment: Separate room for home office activities

RE_WFH_EQUIPMENT_2 Work from home equipment: Laptop or desktop computer provided by employer

RE_WFH_EQUIPMENT_3 Work from home equipment: At least one external monitor available

RE_WFH_EQUIPMENT_4 Work from home equipment: Designated work place where you can leave working material from one day to the other

RE_WFH_EQUIPMENT_5 Work from home equipment: Office chair and table available

RE_WFH_EQUIPMENT_6 Work from home equipment: Permanent, stable and fast internet connection

WFH_IND_AGREE_1 Work from home indicator: Digitization - my job can be done mostly on the computer

WFH_IND_AGREE_2 Work from home indicator: Physical interaction - my job requires phyiscal/interpersonal interaction which cannot be performed via digital channels

WFH_IND_AGREE_3 Work from home indicator: Work context - my job requires a specific work environment (e.g., equipment, safety precautions, working outdoors, etc.)

WFH_IND_AGREE_4 Work from home indicator: Tech savy - I find it easy to work with computers

WFH_IND_SUITABLE_1 How suitable do you consider your main occupation for home office?

WFH_IND_SUITABLE_2 How suitable do you consider yourself as a person for home office?

WFH_IND_SUITABLE_3 How suitable do you consider your residential environment (distraction through family, noise, number of rooms, etc.) for home office?

WFH_IND_SUITABLE_4 How suitable do you consider your home office workstation for home office?

P_PSY_1 Personality inventory: I see myself as someone who does a thorough job

P_PSY_2 Personality inventory: I see myself as someone who is communicative, talkative

P_PSY_3 Personality inventory: I see myself as someone who tends to find fault with others

P_PSY_4 Personality inventory: I see myself as someone who is original

P_PSY_5 Personality inventory: I see myself as someone who often worries

P_PSY_6 Personality inventory: I see myself as someone who is generally trusting

P_PSY_7 Personality inventory: I see myself as someone who tends to be lazy

P_PSY_8 Personality inventory: I see myself as someone who is outgoing, sociable

P_PSY_9 Personality inventory: I see myself as someone who appreciates artistic experiences

P_PSY_10 Personality inventory: I see myself as someone who gets nervous easily

P_PSY_11 Personality inventory: I see myself as someone who performs tasks effectively and efficiently

P_PSY_12 Personality inventory: I see myself as someone who is an environmentally friendly person

P_PSY_13 Personality inventory: I see myself as someone who is reserved

P_PSY_14 Personality inventory: I see myself as someone who is considerate and friendly with others

P_PSY_15 Personality inventory: I see myself as someone who has an active imagination

P_PSY_16 Personality inventory: I see myself as someone who is relaxed, handles stress well

Telework data frame

- `pre` and `lockdown` is `NA` if participants did not work in that period
- `budget`, `free_choice`, `may` and `want` only asked to 'can' population (i.e., `can == "yes"`, otherwise `NA`)
- `current`, `can` and `do` for full survey population (so `0` for `current` and `do` if `can == "no"`)

PRE Telework frequency before pandemic (if worked then)

LOCKDOWN Telework frequency during COVID-related lockdowns (if worked then)

CURRENT Current telework frequency (as of survey date June - August 2023)

BUDGET Max. number of allowed teleworking days (for telework feasible population; i.e. `can == "yes"`)

FREE_CHOICE Free-choice telework frequency (for telework feasible population, i.e. `can == "yes"`)

FEASIBLE Max. feasible telework frequency

CAN Telework feasible? (i.e. no if `feasible == 0`)

MAY Teleworking allowed (for telework feasible population, i.e. `can == "yes"`)

WANT Want to telework (for telework feasbible population, i.e. `can == "yes"`)

DO Do currently telework (as of survey date June - August 2023, i.e. yes if `current != 0`)

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See Also

labels, survey_logic

Examples

```
skimr::skim(survey_intro$main)
```

`survey_logic` *Survey Logic*

Description

The survey flow in Qualtrics did skip some of the question blocks depending on the participants' answers. For such questions we list here who/which population subgroup got the question shown.

Usage

```
survey_logic
```

Format

Data frame

KEY Question key (variable name)

POPULATION Question population: Who got asked this question?

See Also

survey_intro$main

`survey_mto` *Mobility Tool Ownership Stated-Preference Experiment*

Description

Investigates preferences for mobility tool ownership given individual-specific telework preferences.

Usage

```
survey_mto
```

Format

List of data frames:

- `sp`: Main variables of interest for the analysis (see section 'Sp data frame').
- `understood`: Whether the participant understood what the SP attribute implies.
- `timer`: How much time the respondents took to answer.
- `meta`: Some meta information as automatically collected by Qualtrics.

Sp data frame

The unit of observation (each row) is a single choice observation.

UID Unique identifier for respondents

CHOICE_SITUATION Choice situation (1-4)

CA_CHOSEN Whether or not the car alternative was chosen

PT_CHOSEN Whether or not the public transport alternative was chosen

HT_CHOSEN Whether or not the half-fare card was chosen

CS_CHOSEN Whether or not the car sharing alternative was chosen

BI_CHOSEN Whether or not the bicycle was chosen

IS_DRIVER Has driving license for passenger cars (category B); corresponds to `survey_intro$main$mo_driving_license`

WFH Telework frequency

WFA Whether or not work from anywhere is allowed (see also `survey_wfh`$sp)

CA_TYPE Type of the car

CA_FUEL Fuel type

CA_FIXED_COST Car fixed costs including amortization, garaging cost, insurance and taxes. The price of the car is reflected in the fixed cost (amortization).

CA_VARIABLE_COST Car per kilometer cost, including depreciation of the car's value, fuel and energy costs, tire costs and maintenance.

PT_TYPE Public transport travel card type: National or regional season ticket

PT_CLASS Public transport class (1st or 2nd)

PT_FIXED_COST Price of the public transport travel card

PT_ADDITIONAL_ZONE Price of an additional zone included in the regional season ticket

HT_FIXED_COST Price of the half-fare card

BI_TYPE Bicycle type

BI_FIXED_COST Bicycle fixed costs including amortization, maintenance, and insurance. The price of the bicycle is reflected in the fixed cost (amortization).

CS_FREE_FLOATING Car sharing free floating: Whether or not the car sharing is station-based or free-floating

CS_MEMBERSHIP_FEE Car sharing membership fee

CS_TIME_TARIFF Car sharing time tariff

CS_KM_TARIFF Car sharing km tariff

See Also

labels

`survey_wfh`	*Work from Home Stated-Preference Experiment*

Description

Investigates preferences for hybrid work arrangements as well as their implications for telework frequencies. Individuals were tasked to choose between two work arrangements and subsequently state how many days they would like to work from home given the preferred arrangement.

Usage

```
survey_wfh
```

Format

List of data frames:

- `sp`: Main variables of interest for the analysis (see section 'Sp data frame').
- `understood`: Whether the participant understood what the SP attribute implies.
- `timer`: How much time the respondents took to answer.
- `meta`: Some meta information as automatically collected by Qualtrics.

Sp data frame

This data frame is in long format where each row represents a work arrangement (i.e., for each respondent and each choice situation, there are two rows).

UID Unique identifier for respondents

BLOCK Block assigned (from blocked design)

CHOICE_SITUATION Choice situation (1-4)

CHOICE Discrete work arrangement choice (A or B)

FREQUENCY Telework frequency given preferred arrangement

ARRANGEMENT Work arrangement (A or B)

CO_ORDINATION Coordinated presence: Office attendance of team members is coordinated on these days

CORE_HOURS Core hours: Employee can freely allocate working time or is expected to work during regular working hours

HELP_AND_TRAINING Help-desk and training: Help desk for technical assistance and training for effective home office collaboration and management

SALARY_ADJUSTMENTS Salary adjustment: On an hourly wage basis for home office hours.

NK Additional cost: Compensation for increased energy consumption among others.

HARDWARE_BUDGET Hardware budget: Yearly budget for setting up a productive home office work station.

WORK_FROM_ANYWHERE Work from anywhere: Whether or not the remote work location can be freely chosen within Switzerland

DESK_SHARING Restructuring of the office space.

See Also

labels

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CURRICULUM VITAE

PERSONAL DATA

Name	Daniel Heimgartner
Date of Birth	August 22, 1992
Place of Birth	Muri AG, Switzerland
Citizen of	Switzerland

EDUCATION

October 2021 – May 2025	PhD candidate at the Institute for Transport Planning and Systems, *ETH Zürich*, Switzerland
September 2018 – July 2020	MSc in Economics, Double degree track, *University of St. Gallen and Stockholm School of Economics*, Switzerland & Sweden
September 2015 – July 2018	BSc in Sport, Exercise and Health & BA in Economics, *University of Basel*, Switzerland

EMPLOYMENT

June 2020 – June 2021	Internship, *Department II, Financial Stability, Swiss National Bank*, Bern, Switzerland
January 2020 – June 2020	Research intern, *Nepa, Team Data Science*, Stockholm, Sweden
July 2019 – September 2019	Research assistant, *Swiss Institute for Empirical Economic Research*, St. Gallen, Switzerland
October 2012 – April 2013	Military Service, *Mountain Specialist, Center of Excellence for Armed Forces*, Andermatt, Switzerland

PUBLICATIONS

Articles in peer-reviewed journals:

1. Heimgartner D, Axhausen KW (2023d). "Modal Splits Before, During, and After the Pandemic in Switzerland." *Transportation Research Record*, **2678**(7), 1084–1099. doi:10.1177/03611981231212192

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Working papers:

14. Lichtin F, Heimgartner D, Smith KE, Bernauer T, Axhausen KW (2025). “Identifying Acceptable and Effective Behavioral Changes for Climate Change Mitigation.” *Unpublished manuscript*, ISTP, ETH Zürich

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17. Heimgartner D (2024b). **Heimisc***: Heimgartner Miscellaneous*. R package version 0.1.0, URL https://github.com/dheimgartner/Heimisc

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19. Heimgartner D (2025c). **snndata***: Data for the Swiss New Normal*. R package version 0.2.0, URL https://gitlab.ethz.ch/daniehei/snndata

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23. Heimgartner D (2025b). **paperPackage**: *Scaffold an Academic Paper Vignette*. R package version 0.1.0, URL https://github.com/dheimgartner/paperPackage