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

Daniel Heimgartner

IVT, ISTP
ETH Zurich

PhD Thesis Defense
Zurich, June 5th, 2025

Who does not know what telework is?

Who thinks that telework leads to less travel?

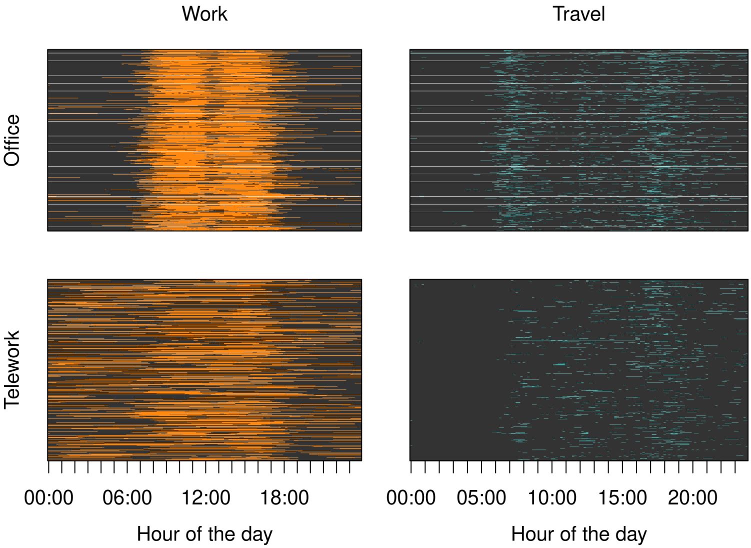
Who does not speak English?

Who thinks that telework leads to less travel?

Wer denkt, dass Home Office zu weniger Verkehr führt?

Motivation

Like it or not – our everyday lives are organized around work



Transport sector as major greenhouse gas emitter

- Transport sector contributes 15% of global greenhouse gas emissions (IPCC, 2022).
- In Switzerland, emissions are substantially higher at 31% (BAFU, 2024).
- Reducing it through policies such as road pricing or fuel taxes is unpopular.
- Behavioral change too...

🍴 Is telework a free lunch? However, evidence on the direction of the effect is mixed (Hook et al., 2020).

IPCC (2022). Climate Change 2022: Mitigation of Climate Change. *Technical report*, Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. BAFU (2024). Kenngrössen zur Entwicklung der Treibhausgasemissionen in der Schweiz 1990–2022. *Technical report*, Bundesamt für Umwelt (BAFU), Bern. Hook A, Court V, Sovacool BK, Sorrell S (2020). A Systematic Review of the Energy and Climate Impacts of Teleworking. *Environmental Research Letters*, **15**(9), 093003.

Why? Second-order effects might offset foregone commutes

- Time flexibility might induce leisure travel.
- Travel chains might become less efficient.
- Teleworkers might be willing to accept longer commutes (de Vos et al., 2018).
  - i.e., they commute less frequently but if they commute, they have to travel further.

Scholarly work over the past decade suggests that telework induces more travel (Wang and Mokhtarian, 2024).

de Vos D, Meijers E, van Ham M (2018). Working From Home and the Willingness to Accept a Longer Commute. *The Annals of Regional Science*, **61**(2), 375–398.
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.

Main research question

Does telework lead to more or less travel in Switzerland?

Measuring and modeling the impact of telework on transport demand.

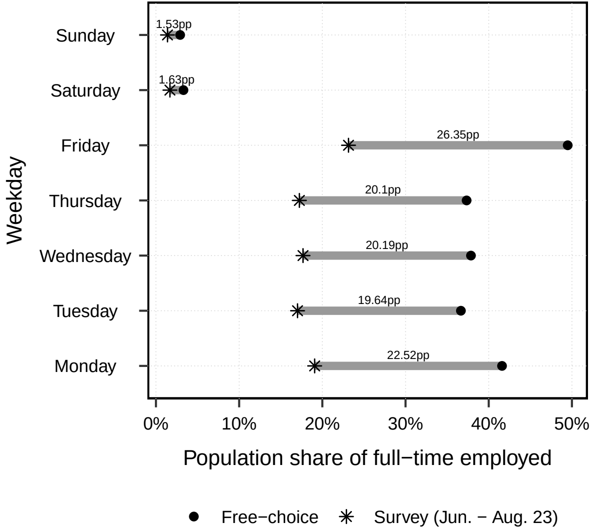
Data

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.

Switzerland's telework landscape and changes brought about by the pandemic

- The pandemic has increased the telework share by 15 percentage points (pp).
  - ...to around 40% (who occasionally telework).
  - Oversupply during COVID (<50% and very high share of fully remote TWers).
- 60% hold teleworkable jobs.
- 91% of them wish to utilize telework.
- Gap of 20 pp exists between those who can work from home and those who actually do.
- About 1/4 of teleworkers desire to telework more frequently, but barriers remain.

Untapped telework potential



- Mondays and Fridays are the preferred days to telework.
- Potential leeway identified by drawing from the empirical distribution of telework frequency across weekdays, based on stated free-choice frequency.

Untapped telework potential between 20 and 30 pp.

Tools

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

The notorious “What if?” question

- There is a (discrete or ordinal) event of interest.
  - The treatment, experiment or intervention.
- Individuals are either untreated or treated.
- Individuals may actively choose, or passively experience the treatment (or not).

Treatment effect: Estimate the effect of that event on an (individually-experienced, then aggregated) outcome of interest.

Treatment	Outcome
Wearing a helmet while cycling	Injury severity
Buying a fuel-efficient car	CO_2 emissions or vehicle-miles driven
Doing a PhD at ETH Zurich	Achieving career success

? With cross-sectional data, we only observe people as either treated or untreated (their factual state at the time of measurement) – we never observe them in the opposite (counterfactual) state! “What if?”

Mokhtarian PL (2024). The Insidious Problem of Selection Biases: How to Recognize Them, and What to Do About Them? Talk at the *MIT Mobility Initiative*, https://www.youtube.com/watch?v=n1cbWuShESk&t=3061s&ab_channel=MITMobilityInitiative.

A case of a selection bias

This would be fine, if the treatment were randomly assigned (RCT).
$\Rightarrow \; TE = \mathbb{E}[Y|\text{treated}] - \mathbb{E}[Y|\text{untreated}]$

? But what if the treated group differs from the untreated group in ways that are relevant to the outcome? $\Rightarrow$ Selection bias!

Treatment	**Self-selection**
Those choosing to wear a helmet	may be safer cyclists
Those buying a fuel-efficient car	may want to travel more
Those doing a PhD at ETH Zurich	may be losers in the first place

Separate the treatment effect from the pre-existing differences. These pre-existing differences may be observed (X; "selection on observables") or unobserved (ϵ; "selection on unobservables")!

What the heck, man! So, what's the solution?

Heckman J (1979). Sample Selection Bias as a Specification Error. *Econometrica*, **47**(1), 153–161.

The solution: OPSR – a form of endogenous switching regression model

- Model the (ordered) treatment adoption (“selection process”) and the treatment outcome (“outcome process”) simultaneously and account for observable AND unobservable pre-existing differences.

$\Rightarrow$ $TE = \mathbb{E}[Y|X, \text{treated}] - \mathbb{E}[Y|X, \text{untreated}] + \text{correction term}$

- OPSR = Ordered probit model + Continuous outcome model + Error correlation
- Similar to a latent class model where class label is observed and the two processes aren’t independent.

$\Rightarrow$ Probabilities of the two processes cannot simply be multiplied!

⚠ $P_{\text{OPSR}} \neq \sum_{\text{treatment}=j}^{J} P(j)P(Y|j)$

The log-likelihood function

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

where…

The conditional expectation

(OLS: $\mathbb{E}[y_j] = \boldsymbol{X_j}\beta_j$)

$$\begin{aligned}\mathbb{E}[y_j \mid Z = j] &= \boldsymbol{X_j}\beta_j + \mathbb{E}[\eta_j \mid \kappa_{j-1} - \boldsymbol{W}\gamma < \epsilon \leqslant \kappa_j - \boldsymbol{W}\gamma] \\ &= \boldsymbol{X_j}\beta_j - \rho_j\sigma_j \frac{\phi(\kappa_j - \boldsymbol{W}\gamma) - \phi(\kappa_{j-1} - \boldsymbol{W}\gamma)}{\Phi(\kappa_j - \boldsymbol{W}\gamma) - \Phi(\kappa_{j-1} - \boldsymbol{W}\gamma)}\end{aligned} \tag{2}$$

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

$$\mathbb{E}[y_{j'} \mid Z = j] = \boldsymbol{X_{j'}}\beta_{j'} - \rho_{j'}\sigma_{j'} \frac{\phi(\kappa_j - \boldsymbol{W}\gamma) - \phi(\kappa_{j-1} - \boldsymbol{W}\gamma)}{\Phi(\kappa_j - \boldsymbol{W}\gamma) - \Phi(\kappa_{j-1} - \boldsymbol{W}\gamma)} \tag{3}$$

If $\rho_j \neq 0$ and/or $\rho_{j'} \neq 0$ then the treatment effect is not simply $\boldsymbol{X_j}\beta_j - \boldsymbol{X_{j'}}\beta_{j'}$ but

$$\mathbb{E}[y_j \mid Z = j] - \mathbb{E}[y_{j'} \mid Z = j] = \boldsymbol{X_j}\beta_j - \boldsymbol{X_{j'}}\beta_{j'} + \text{correction term} \tag{4}$$

Translating math to code

What do we want?

- Easily and flexibly specify the processes ($\boldsymbol{X}_j\beta_j$ and $\boldsymbol{W}\gamma$).
- Estimate the parameters.
- Summarize the model results.
- Easily and iteratively update the model.
- Compare the models.
- Compute (counterfactual) conditional expectations and thus treatment effects.
- Summarize and visualize the treatment effects.
- Publication grade output tables.

We want it now and we want it to be fast!

Enters: The **OPSR** R-package

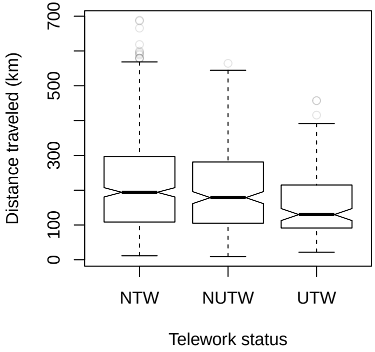
Available on CRAN now.*

*Disclaimer: The current CRAN release is outdated and has some 🐞's (among others a memory leak). The updated version has not yet been released... But is available from the `dev` branch here: `https://github.com/dheimgartner/OPSR/tree/dev`.

Analysis

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 A: Policy and Practice*, to be transferred.

What if current teleworkers were not teleworking?



- TimeUse+ tracking data from 879 individuals (2022-07-18 – 2023-02-09).
- Infer telework status from time-use diary (tracked telework episodes).
  - Non-teleworkers (NTWers; N=492)
  - Non-usual teleworkers (NUTWers; <3 days/week; N=259)
  - Usual teleworkers (UTWers; 3+ days/week; N=128)
- Infer weekly kilometers traveled (across all modes).
- Use the OPSR methodology to get unbiased treatment effects.

OPSR script

```
R> f <- 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 + educ_higher + hh_size + married + freq_onl_order + res_loc +
+    workload
R> fit <- opsr(f, data, weights = weights)
R> summary(fit)
R> opsr_te(fit, type = "unlog-response")
R> plot(fit, type = "unlog-response")
```

R> summary(fit)

```
R> print(summary(fit), print.call = FALSE)
BFGS maximization, 344 iterations
Return code 0: successful convergence
Runtime: 3.26 secs
Number of regimes: 3
Number of observations: 879 (492, 259, 128)
Estimated parameters: 71

Log-Likelihood: -1015.052
AIC: 2172.104
BIC: 2511.398
Pseudo R-squared (EL): 0.3053
Pseudo R-squared (MS): 0.2095
Multiple R-squared: 0.6136 (0.6419, 0.6553, 0.3222)
...
```

Wald test suggests that there is error correlation

```
Estimates:
                         Estimate Std. error t value  Pr(> t)
kappa1                   2.386065   0.755027   3.160 0.001576 **
kappa2                   3.601433   0.754574   4.773 1.82e-06 ***
s_teleworkability        0.253970   0.035869   7.080 1.44e-12 ***
...
o1_(Intercept)           2.888933   0.306988   9.411  < 2e-16 ***
...
sigma1                   0.393013   0.020533  19.141  < 2e-16 ***
sigma2                   0.411519   0.038681  10.639  < 2e-16 ***
sigma3                   0.462633   0.063710   7.262 3.83e-13 ***
rho1                     0.186624   0.422601   0.442 0.658774
rho2                     0.502810   0.096370   5.217 1.81e-07 ***
rho3                     0.198015   0.396531   0.499 0.617520
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Wald chi2 (null): 1647.465 on 60 DF, p-value: < 0
Wald chi2 (rho): 27.4168 on 3 DF, p-value: < 0
```

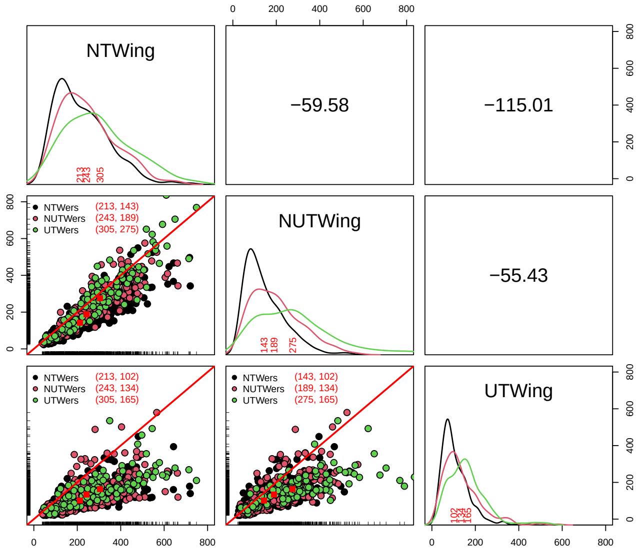
$$\mathbb{E}[y_j \mid Z = j] = \boldsymbol{X_j}\boldsymbol{\beta_j} - \rho_j \sigma_j \frac{\phi(\kappa_j - \boldsymbol{W\gamma}) - \phi(\kappa_{j-1} - \boldsymbol{W\gamma})}{\Phi(\kappa_j - \boldsymbol{W\gamma}) - \Phi(\kappa_{j-1} - \boldsymbol{W\gamma})}$$

https://github.com/dheimgartner/thesisSlides/blob/main/vignettes/figures/heckman-would-be-proud.gif

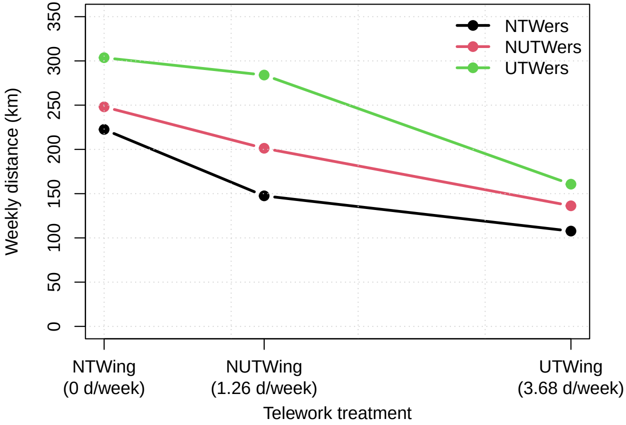
R> opsr_te(fit, type = "unlog-response")

```
Treatment Effects

TE

            G1           G2           G3
T1->T2  -69.91 ***  -54.01 ***  -29.52 ***
T1->T3 -110.98 *** -109.34 *** -139.91 ***
T2->T3  -41.07 ***  -55.33 *** -110.39 ***


ATE

   T1->T2      T1->T3      T2->T3
1  -59.58 *** -115.01 ***  -55.43 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
R> plot(fit, type = "unlog-response")
```



Telework treatment effects



- Counterfactual weekly km traveled are very different.
- Telework reduces travel of a particularly mobile group (with longer commutes).
- Unit treatment effects indicate that travel reduction roughly corresponds to 2-way commute distance.
- Travel reduction amounts to 16% (aligns with Sallard, 2024).
- Descriptive analysis shows, that time allocation is very similar across the TWer groups – except for travel.

⚠ Not accounting for error correlation underestimates treatment effects.

Sallard A (2024). *Mobility, Population, and Social Spaces: Understanding Travel Demand in a Changing World.* Ph.D. thesis, ETH Zürich, Zürich

Conclusion

Takeaways

- Telework changes travel by cutting commutes and shifting trips from the central business district (CBD) to home.
  - Result: 16% less travel and more dispersed trip timing and locations.
  - Mobility tool ownership and mode shares stay stable.
- Switzerland still has 20 pp untapped telework potential on any weekday.
- Mixed effects reported in the literature may stem from selection bias when using cross-sectional data.
- The **OPSR** package makes replicating this analysis simple.
- It also opens doors for broader applications beyond transportation.

Selection bias is widespread and can mislead policy – addressing it is crucial.

Thank you!

Appendix

Limitations

- The case of Switzerland (but: **OPSR** to easily replicate the analysis, e.g., based on national census).
- Multivariate normal only one possible error distribution.
  - Distributional assumptions should be checked (but how? ϵ is latent).
  - Copula modeling (but no unified framework – at least not in R).
- Backward selection (starting from an overfitted model) and identification issues.
- Why not leveraging the panel structure?
  - Telework is used very opportunistically and flexibly (varies over the weeks).
  - Unobserved factors that influence this (short-term) decision and VMD.
  - $\Rightarrow$ Greetings from Heckman!
- Commute distance as explanatory variable?
- Arbitrary classification of teleworker groups (NTWers, NUTWers, UTWers).
- Incomplete understanding of employer-side (simplified modeling of telework adotion).
- LOL value proposition: Reinventing the wheel (**OPSR**).

Long-standing interest in the relation between telework and transport demand

- Telework shares quadrupled during the pandemic (Barrero et al., 2023).
- First paper: Mobility changes brought about by the pandemic.
  - Adjustments to the extraordinary circumstances were not made habitual (e.g., not a change in underlying preferences, but “applying” these preferences in a new environment).
- Telework as the lasting legacy of the pandemic reignited the interest.

⚖ However: Evidence on the direction of the effect is mixed (Hook et al., 2020).

Barrero JM, Bloom N, Davis SJ (2023). The Evolution of Work From Home. *Journal of Economic Perspectives*, **37**(4), 23–50. Hook A, Court V, Sovacool BK, Sorrell S (2020). A Systematic Review of the Energy and Climate Impacts of Teleworking. *Environmental Research Letters*, **15**(9), 093003.

Data, tools and analysis

Data

- Three stage survey instrument (fielded after the pandemic).
- Understand the (evolution of the) telework landscape in Switzerland.
- Two stated preference experiments.
  - Leverage of employer-side incentives (hybrid work arrangements).
  - Impact of telework on mobility tool ownership (previously neglected second-order effect).

Tools

- Suitable modeling framework.
- Implementation thereof in R.

Analysis

- Applying the tools to
- TimeUse+ data (time-use and travel diary data using a smartphone tracking app).

Rich data source to investigate telework in Switzerland.

Data, tools and analysis

Data

- Three stage survey instrument (fielded after the pandemic).
- Understand the (evolution of the) telework landscape in Switzerland.
- Two stated preference experiments.
  - Leverage of employer-side incentives (hybrid work arrangements).
  - Impact of telework on mobility tool ownership (previously neglected second-order effect).

Tools

- Suitable modeling framework.
- Implementation thereof in R.

Analysis

- Applying the tools to
- TimeUse+ data (time-use and travel diary data using a smartphone tracking app).

OPSR statistical software.

https://cran.r-project.org/package=OPSR

Data, tools and analysis

Data

- Three stage survey instrument (fielded after the pandemic).
- Understand the (evolution of the) telework landscape in Switzerland.
- Two stated preference experiments.
  - Leverage of employer-side incentives (hybrid work arrangements).
  - Impact of telework on mobility tool ownership (previously neglected second-order effect).

Tools

- Suitable modeling framework.
- Implementation thereof in R.

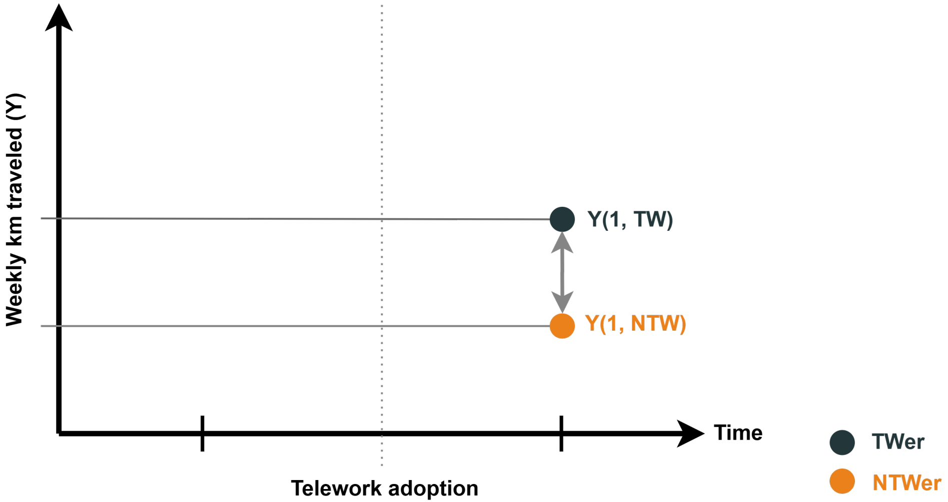
Analysis

- Applying the tools to
- TimeUse+ data (time-use and travel diary data using a smartphone tracking app; Winkler et al., 2024).

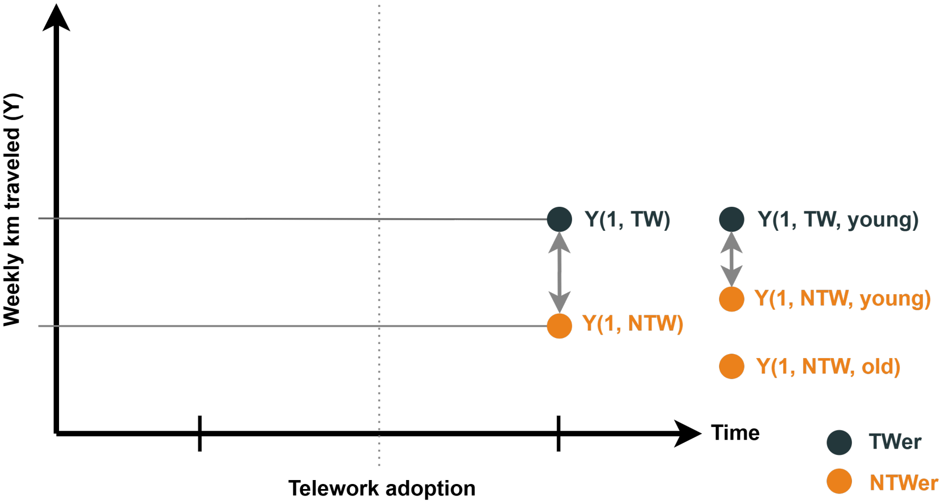
Estimating telework treatment effects leveraging RP data and being mindful of selection bias.

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.

Wrong (group comparison)



Still wrong (controlling for observables)



Right but not observable (longitudinal estimate)

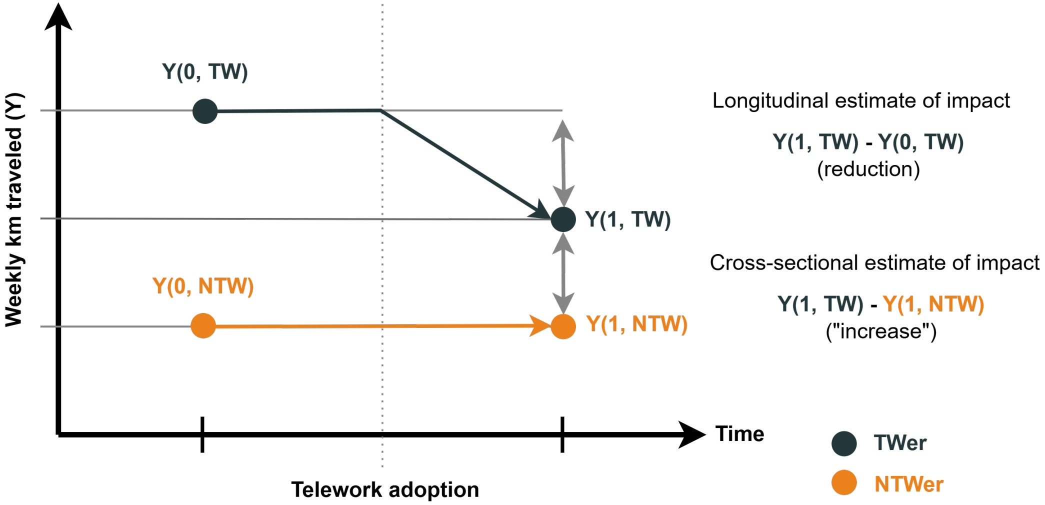
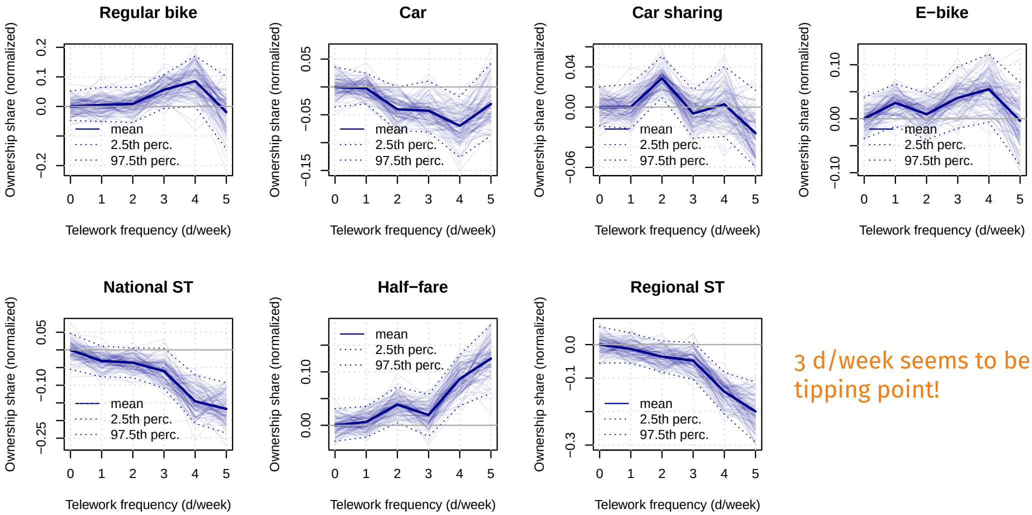


Figure based on: Wang X, Mokhtarian PL (2024). Examining the Treatment Effect of Teleworking on Vehicle-Miles Driven: Applying an Ordered Probit Selection Model and Incorporating the Role of Travel Stress. *Transportation Research Part A*, **186**, 104072.

Implications for mobility tool ownership



3 d/week seems to be the tipping point!

OPSR vs. indicator variable approach

Indicator approach (assuming no interactions)

- Weekly km traveled is a function of X ($Y(X)$).
- Telework is exogenous – i.e., there are no factors simultaneously influencing telework and the error term $\Rightarrow$ Level effects.

Treatment effect is simply the level effect of the telework indicator. However, (all!) parameter estimates might be biased!

OPSR

- Weekly km traveled is a function of X but the effect of x depends on telework status J ($Y(X|J)$).
  - For example: The effect of having children on weekly km traveled might be different for NTWers (bring children to school as part of the commute) and UTWers (extra trip).
- Telework is endogenous – i.e., there are (unobserved) factors simultaneously influencing telework adoption and weekly km traveled.

Treatment effect is a result of 1. different parameters/process specifications for the groups (i.e., the $X_j\beta_j$) and $X_{j'}\beta_{j'}$ and 2. the selection on unobservables (IMR term; see Equations 2 and 3).

Telework treatment effects

	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

Telework unit treatment effects

	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

Unit treatment effects (UTE) are computed by dividing the TE (from Page 46) by the difference in telework frequency.

Not accounting for error correlation underestimates the treatment effects

	Treatment	Telework status			ATE
		NTWers	NUTWers	UTWers	
OPSR	NTWing→NUTWing	-69.911	-54.006	-29.523	-59.576
	NTWing→UTWing	-110.981	-109.338	-139.912	-115.009
	NUTWing→UTWing	-41.070	-55.332	-110.390	-55.433
Rho = 0	NTWing→NUTWing	-38.245	-40.882	-47.310	-40.323
	NTWing→UTWing	-94.319	-85.610	-107.308	-94.063
	NUTWing→UTWing	-56.074	-44.728	-59.998	-53.740
Δ	NTWing→NUTWing	-31.666	-13.124	17.787	-19.253
	NTWing→UTWing	-16.662	-23.728	-32.605	-20.946
	NUTWing→UTWing	15.004	-10.605	-50.392	-1.692
%	NTWing→NUTWing	-45.295	-24.300	60.249	-32.317
	NTWing→UTWing	-15.013	-21.702	-23.304	-18.212
	NUTWing→UTWing	36.534	-19.166	-45.649	-3.053