Is teleworking always a “treatment” for reducing distance traveled?

Investigating the roles of telework motivations and frequency using multinomial switching regression models

Xinyi Wang and Patricia L. Mokhtarian

September 14, 2022

Technical University of Munich

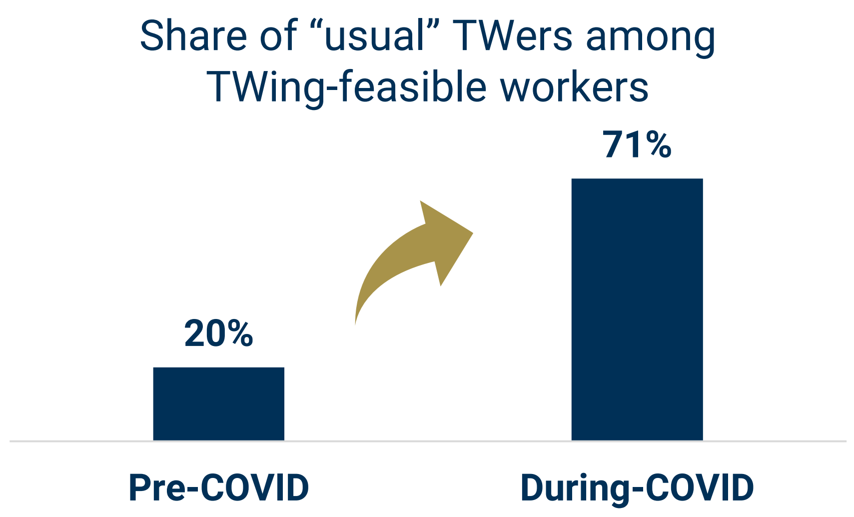
Activity-Based Modeling Symposium

Seeon, Germany

Georgia Tech

Background

- **Teleworking is a major lifestyle change that was widely adopted during the pandemic.**
- **Many employers now want workers back in the office, while employees want to keep working from home.**
- **Permanent teleworking options and hybrid work are trendy.**



Source: Parker, Horowitz, & Arditi (2020)

Post-COVID new normal:
the long tail of COVID-generated teleworking

Georgia Tech

Some potential (COVID-induced) impacts on personal travel

- Some related mostly to WFH, others may be broader
- They are not equally likely or equally impactful
- There will be local variations
- ***Multiple factors will counteract each other***

Post-COVID changes	vehicle-miles	vehicle-trips
More WFH	↘	↘
Impact on nonwork travel?	?	?
Longer commute distances	↗	↘
Higher vehicle ownership	↗	↗
Lower transit share	↗	↗
More long-distance auto travel?	↗	↗

Considering all the changes due to teleworking, will it reduce the total distance traveled on net?

- **Objective: quantify and compare the impact of teleworking (TW) on (self-reported) weekly vehicle-miles driven (VMD)**
- Compare for different types of workers, classified by
  - Teleworking **frequency** category *(non-, non-usual, usual)*
  - Teleworking-related **motives** *(travel-stressed or not)*
- Calculate unbiased ***"treatment effects"*** of teleworking
- Accounting for ***self-selection biases***

Georgia Tech

Outline

Data description: online survey

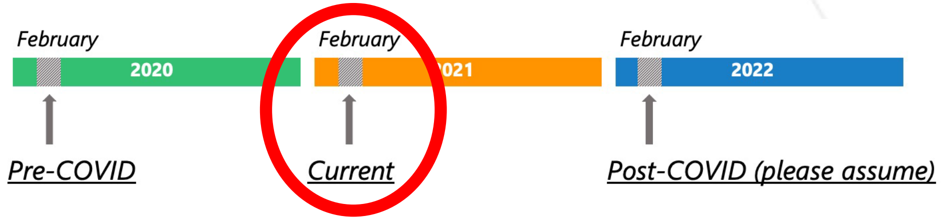
Methodology: model & treatment effects

Treatment effect: general patterns by TW freq. cat. (NTW, NUTW, UTW)

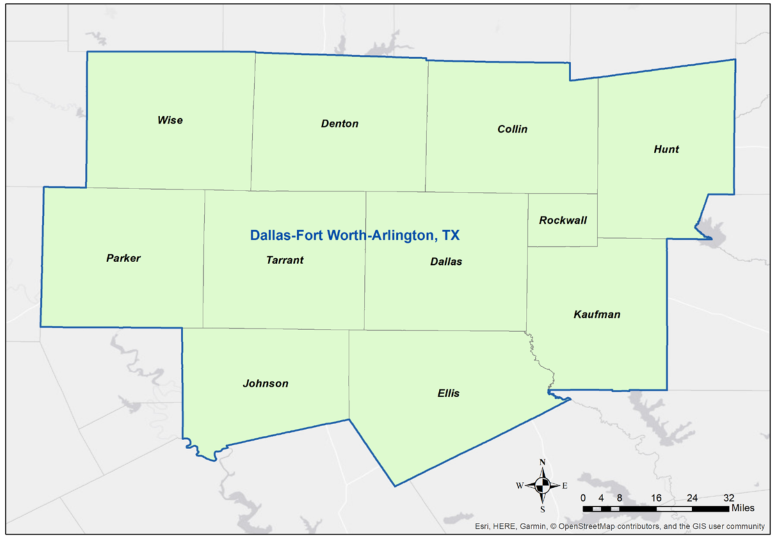
Treatment effect: considering teleworking motives (esp. travel stress)

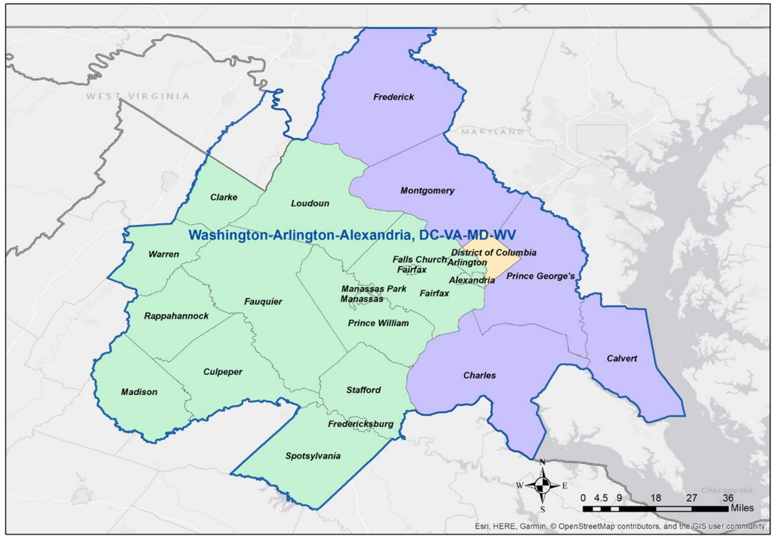
Conclusions & next steps

Online survey overview



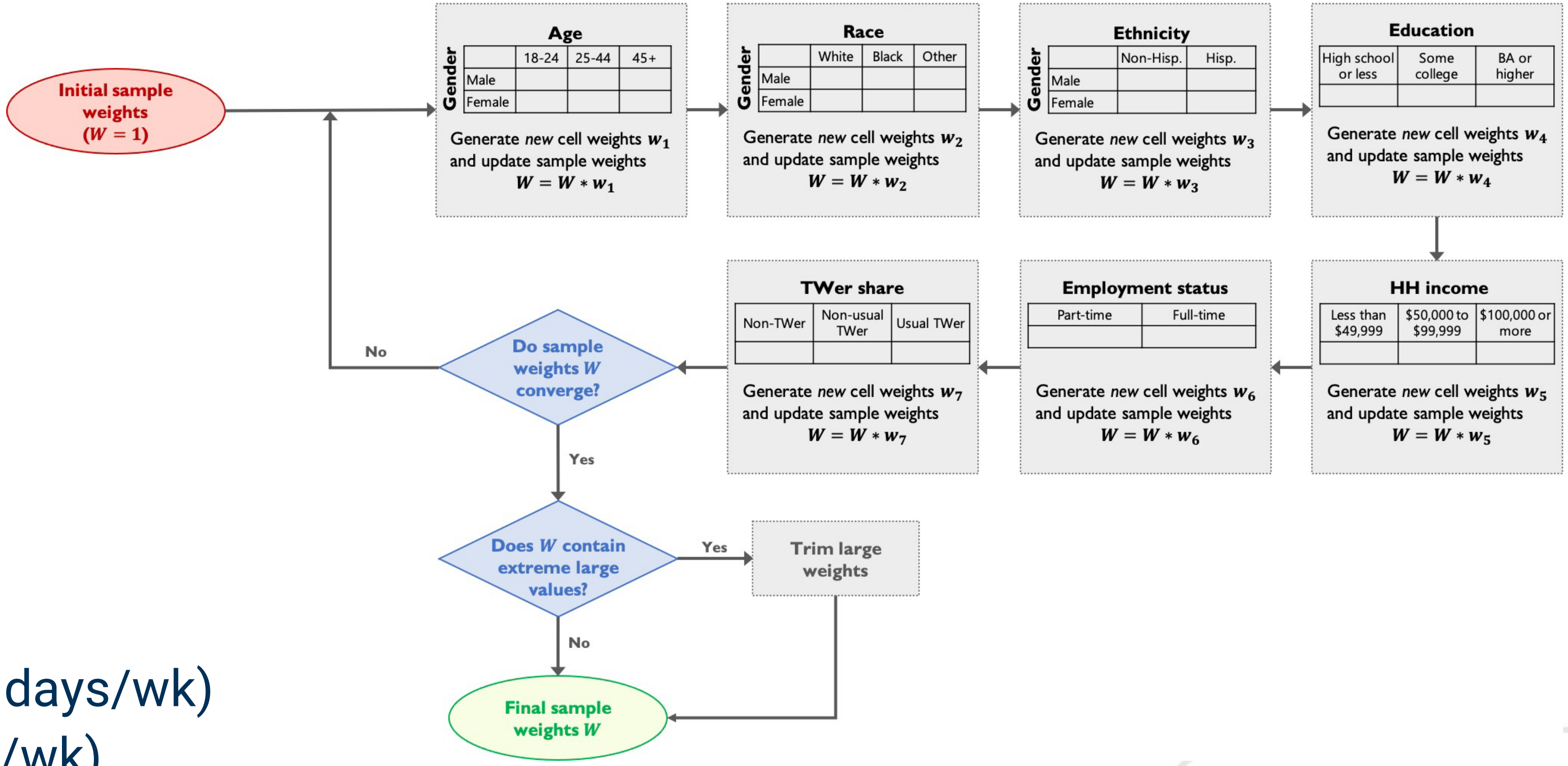
- **Funded by Cintra (Ferrovial)**
  - Impact of COVID-influenced TW on toll revenues
- **Survey focus**
  - Telework and work patterns **before**, **during**, and **after** COVID-19
- **Study areas**
  - Dallas-Fort Worth-Arlington (DFA)
  - Washington-Arlington-Alexandria (WAA)
- **Respondent sources**
  - Cintra database (DB): current and potential customers who consented to be surveyed
  - Online panel (OP): three vendor companies
- **Data collection Feb. 24 - April 30, 2021**





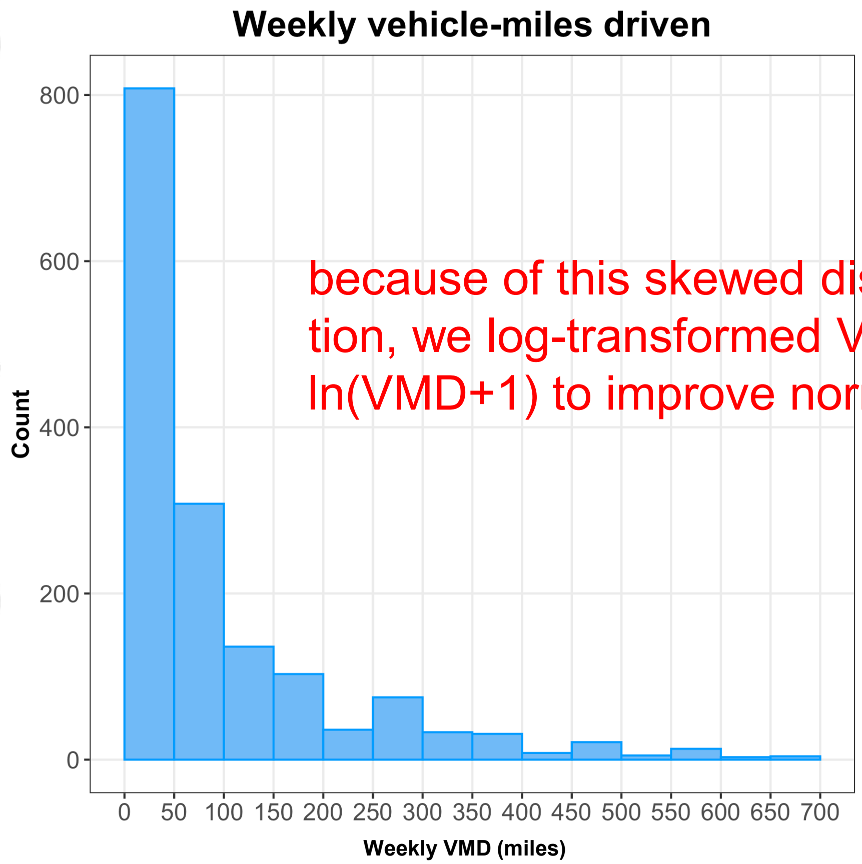
Sample weights

- Sample was weighted (by region) to reflect pop. distributions on:
  - Gender
  - Age
  - Race
  - Ethnicity
  - Education
  - HH income
  - Employment status
  - Pre-COVID shares of
    - Non-TWers
    - “Non-usual” TWers (< 3 days/wk)
    - “Usual” TWers (3+ days/wk)



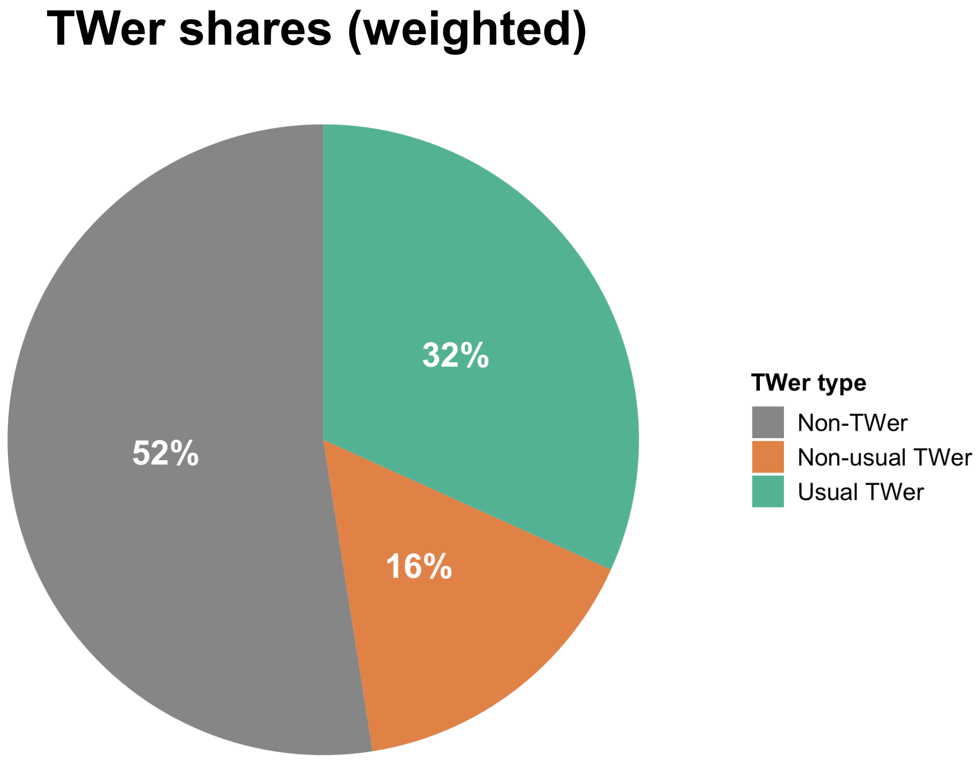
Working sample size N = 1,584

- **Data inclusion criteria**
  - Employed, but not self-employed
  - One-way commute distance ≤ 70 mi
  - Weekly VMD ≤ 700 mi



because of this skewed distribution, we log-transformed VMD → ln(VMD+1) to improve normality

- **Teleworking frequency**
  - **Non-TWer:** never teleworks
  - **Non-usual TWer**: teleworks < 3 times/wk
  - **Usual TWer:** teleworks ≥ 3 times/wk



A tale of two types of travel diary studies of TWing

TW program evaluations

- Early (1980s – 1990s)
- Small, unrepresentative samples
- Focused on TWing
- Panel data (before-after)
- ***Found travel reductions*** *(TW **decreased** travel)*

General travel surveys

- Later (2000s – 2010s)
- Large, representative samples
- No emphasis on TWing
- Cross-sectional data
- ***Finding complementarity*** *(TW **increases** travel)*

Georgia Tech

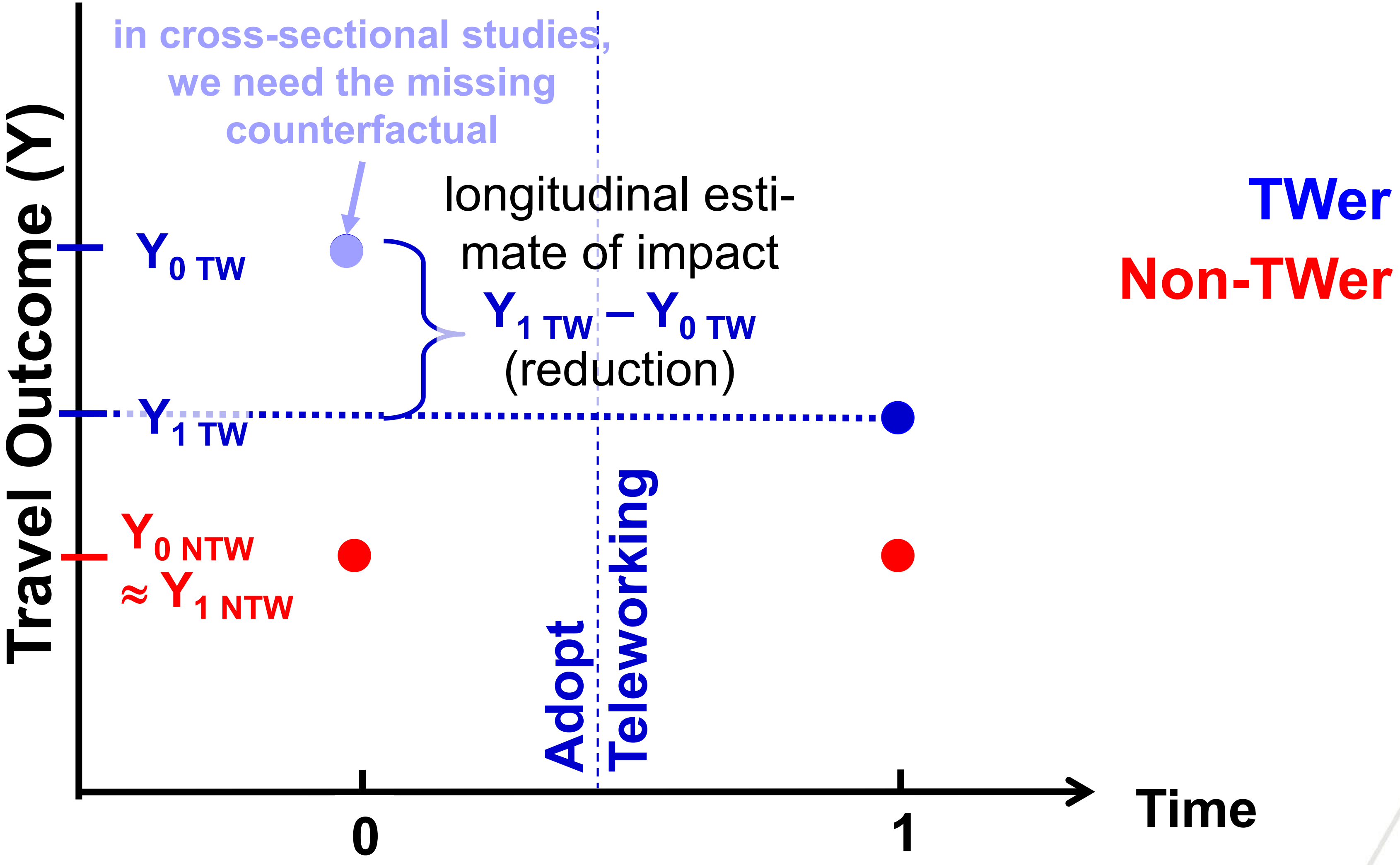
Mokhtarian et al. 1995; He & Hu 2015; Kim et al. 2015; Zhu 2013; Zhu & Mason 2014

Why the difference?

- **Our suspicion:** TWers differed from "observationally equivalent" non-TWers (in ways that caused them to travel more) *even before starting to TW*
  - In more autonomous occupations?
  - More work-related travel?
  - More active non-work lifestyle?
  - More risk-taking, adventure-seeking?
- What if TWing reduced their travel from "far above average" to merely "above average"?
- In a cross-sectional study, it would appear only that TWers travel more than non-TWers, implying complementarity

Georgia Tech

Longitudinal v. cross-sectional inference



Enter the endogenous switching regression model (ESRM)

- **Designed to deal with self-selection bias…**
  - Unobserved factors that influence ***teleworking adoption & frequency*** may also influence ***how much a person drives***. Again, for example:
    - In more autonomous occupations?
    - More work-related travel? More active non-work lifestyle?
    - More risk-taking, adventure-seeking?
  - In such cases, a conventional regression approach will yield ***biased parameters***
- **… in a *cross-sectional* setting, where we only observe people in one state**
- **And want to obtain an unbiased estimate of the *effect of treatment* (*TWing frequency*, here) on the *outcome of interest* (*VMD*, here)**
- **Traditional ESRM only deals with *binary* states: *treated* or *untreated***
- **We have three states: *not TWing, non-usual TWing, and usual TWing***

Georgia Tech

Key components of a *binary selection* ESRM

- **A selection model** (binary probit):
  - $Telework\ adoption\ propensity = \boldsymbol{W\gamma} + \varepsilon$
  - $\boldsymbol{W}$ = explanatory variables, $\boldsymbol{\gamma}$ = coefficients, ε = error term
- **Two outcome models** (linear regressions):
  - If teleworking ("treated"): $\ln(VMD + 1) = \boldsymbol{X\beta_1} + \eta_1$
  - If not teleworking ("untreated"): $\ln(VMD + 1) = \boldsymbol{X\beta_2} + \eta_2$
  - $\boldsymbol{X}$ = explanatory variables, $\boldsymbol{\beta_1}, \boldsymbol{\beta_2}$ = coefficients, η_1, η_2= error terms
- **Trivariate normal assumption** for the error term distribution:

$$\begin{bmatrix} \varepsilon \\ \eta_1 \\ \eta_2 \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho_1\sigma_1 & \rho_2\sigma_2 \\ \rho_1\sigma_1 & \sigma_1^2 & 0 \\ \rho_2\sigma_2 & 0 & \sigma_2^2 \end{bmatrix} \right)$$

Georgia Tech

Multinomial logit switching regression (MNLSR) model

- **A selection model** (multinomial logit, MNL):
  - Probability of TWing category t being selected:

$$P^t = P\left(U_t \geq \max_{\substack{t\prime\in T \\ t\neq t\prime}} U_{t\prime}\right) = \frac{e^{V_t}}{\sum_{t\prime\in T} e^{V_{t\prime}}}$$

  - $U_t = V_t + \varepsilon_t = \boldsymbol{W}\boldsymbol{\gamma}_t + \varepsilon_t, \quad t, t' \in T = \{N, NU, U\}$
  - $\boldsymbol{W}$ = explanatory variables, $\boldsymbol{\gamma}_t$ = coefficients , $\epsilon_t \overset{i.i.d.}{\sim} Gumbel\left(0, \frac{\lambda^2}{2}\right)$
- **An integrated outcome model with group-specific coefficients** (linear regression):

$$\ln(VMD + 1) = \mathbf{1}_N(t) \cdot \boldsymbol{X}_N\boldsymbol{\beta}_N + \mathbf{1}_{NU}(t) \cdot \boldsymbol{X}_{NU}\boldsymbol{\beta}_{NU} + \mathbf{1}_U(t) \cdot \boldsymbol{X}_U\boldsymbol{\beta}_U + \eta$$

  - $\boldsymbol{X}_N, \boldsymbol{X}_{NU}, \boldsymbol{X}_U$= explanatory variables, $\boldsymbol{\beta}_N, \boldsymbol{\beta}_{NU}, \boldsymbol{\beta}_U$= coefficients, $\eta \sim N\ (0, \sigma^2)$
- **Connecting the selection and outcome models**:

$$\mathbb{E}[\eta|\ t] = \sum_{\substack{t'\in T \\ t'\neq t}} \alpha^{t'} \cdot \frac{P^{t'}}{1-P^{t'}} lnP^{t'} - \alpha^t \cdot\ lnP^t$$

  - $\alpha^{t'}$ is the scaled correlation between η and $\epsilon_{t'}$

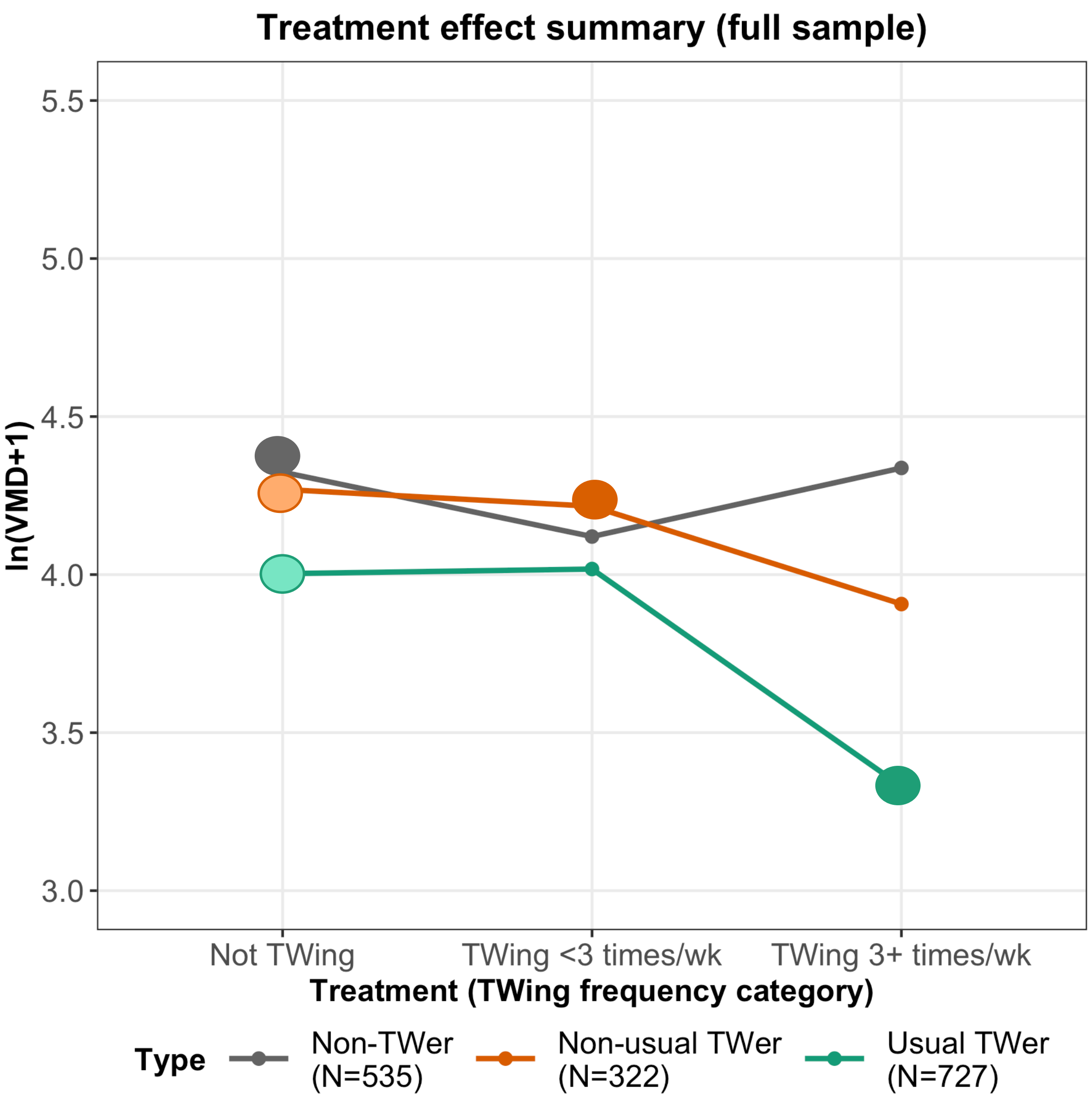
Dubin & McFadden 1984; Dubin 1982

fact. = factual
cfact. = counterfactual

Calculation of treatment effects (TEs)

Treatment	Observed untreated group: NTWer	Observed NUTW-treated group: NUTWer	Observed UTW-treated group: UTWer
A: If untreated (i.e., if a NTWer)			
B: If NUTW-treated (i.e., if a NUTWer)			
C: If UTW-treated (i.e., if a UTWer)			
B-A			
C-A			
C-B			

Full sample model (2 treatments: NUTWing & UTWing)



- Focusing on the TEs (compared to not TWing) for the two observed TWer groups:
  - ●, ● = factual
  - ●, ● = (NTW) counterfactual
- **VMD of non-usual TWers (16% of the sample) barely declines**
- **VMD of usual TWers (32% of the sample) declines substantially**
- **On net, then, VMD declines for TWers**

So far, so good, but…

- In preliminary explorations, counterintuitive results kept popping up
  - Reminiscent of various unexpected results when using similar methods to quantify the ***effect of the built environment on travel behavior***, in the presence of ***residential self-selection***
- Going back to the original *conceptual* rationale of the ESRM:
  - "The latent index [of the selection model] has the interpretation of the ***expected net utility derived from receiving treatment***; individuals participate in a program [are treated] if net utility is positive (or nonnegative) and do not participate if net utility is negative" (Heckman et al., 2001, p. 211).
  - "Embodied in this concept [selectivity bias] is the notion that ***agents choose among competing alternatives at least in part on the basis of anticipated incremental returns.*** Rationality dictates that persons choosing a given alternative do so because ***they … [expect] a more favorable return than those who choose otherwise…*** (Nakosteen and Zimmer, 1980, p. 840)

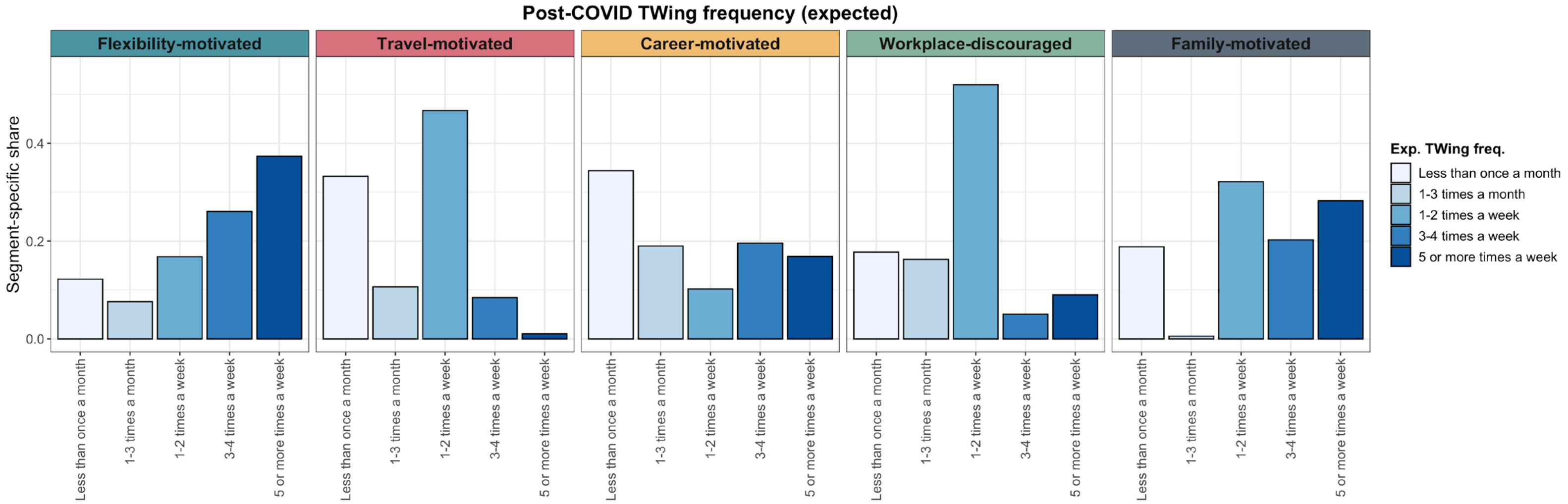
Georgia Tech

So far, so good, but… (cont'd)

- In classic applications, the ***outcome equation*** explicitly measures the return (or benefit) of interest
  - In economics, the ***treatment*** may be "getting a college education", and the ***outcome*** is wages
  - In agricultural economics, the ***treatment*** may be a new fertilizer, and the ***outcome*** is crop yield
  - In such cases, it's logical to presume that ***people choose the treatment*** (or decline it) ***if they think it will improve their return***
- **But is VMD the "return" that people necessarily want to improve when they decide whether or not to telework?**

Is VMD the best measure of benefit for all TWers?

- For **travel-stressed individuals**, the key teleworking motive may relate to reducing travel – VMD is likely a good measure of the teleworking outcome
- **However, reducing travel is not the only motive for all TWers**
- In another study, we identified five teleworking-related motives by applying a latent class TW frequency model (Wang et al., 2022)
  - **Flexibility-motivated**
  - **Travel-motivated**
  - **Career-motivated**
  - **Workplace-discouraged**
  - **Family-motivated**

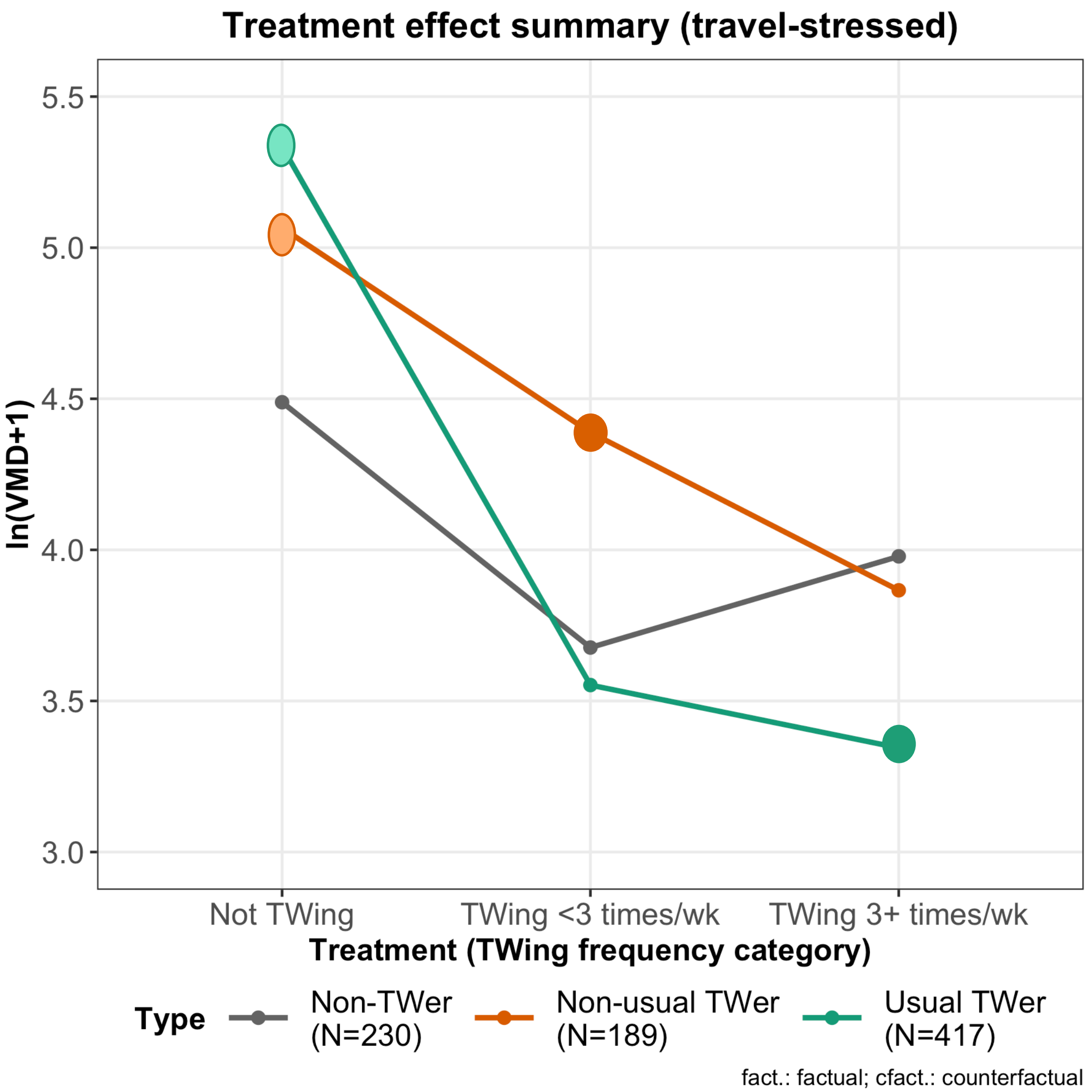


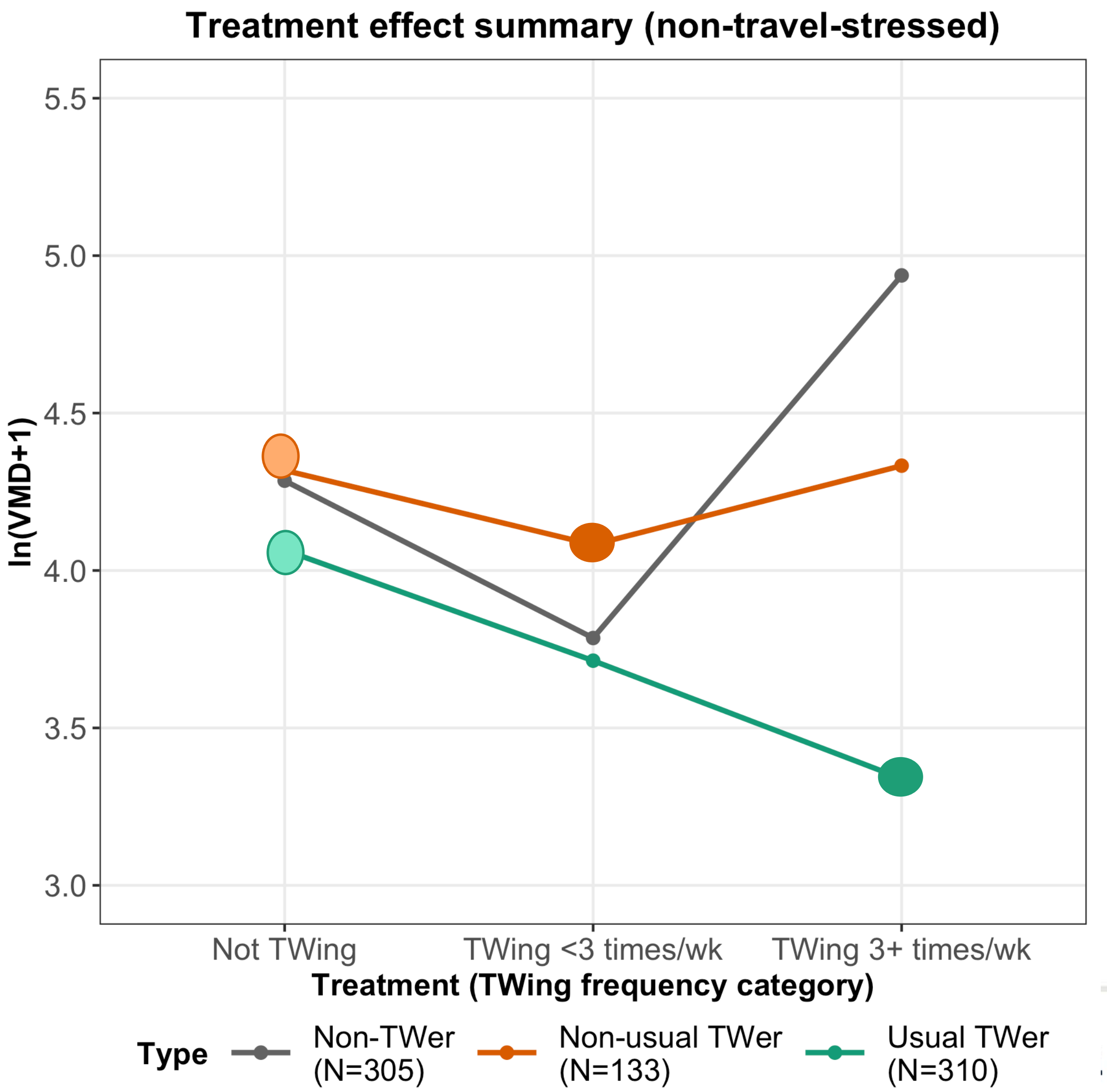
Is VMD the best measure of benefit for all TWers? (cont'd)

- **TWers with other motives** may have **different travel patterns** compared to travel-stressed TWers. For example:
  - ***Those who TW to have more time for family duties*** may have more/ longer non-work trips
  - ***Those who TW to relocate to suburban areas*** may commute less often, but with longer distances
- Mixing all TWers together will mask the heterogeneity residing in the VMD outcome of the TWing treatment
- Based on attitudes, we separated the full working sample into
  - **Travel-stressed (N=836 [53%], avg. VMD = 122.9 mi)**
  - **Non-travel-stressed (N=748 [47%] , avg. VMD = 105.8 mi)**

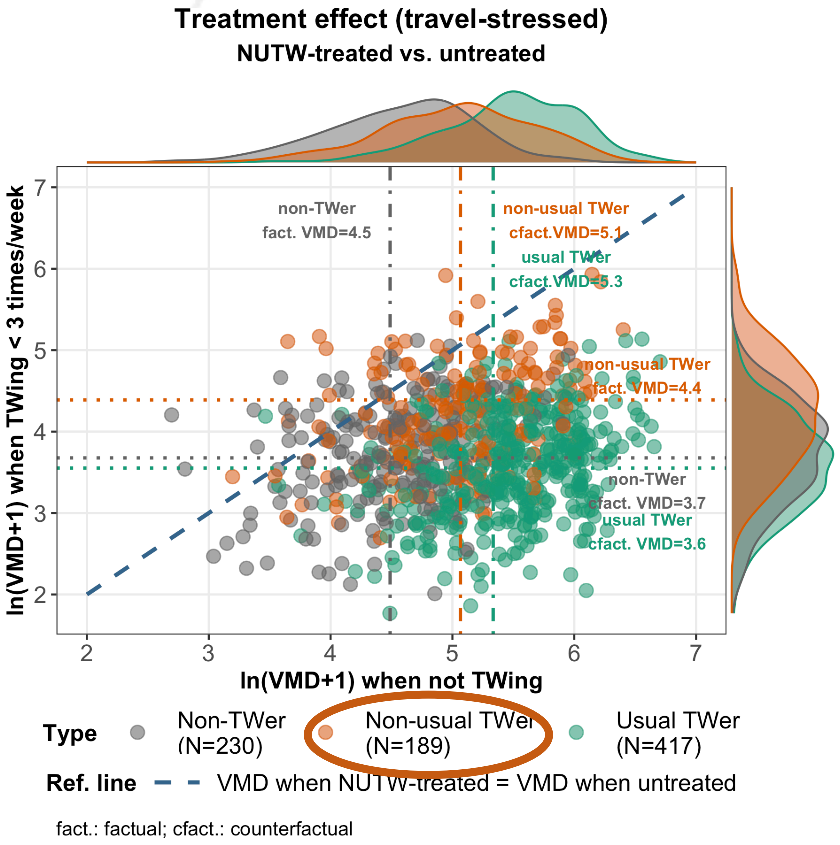
Georgia Tech

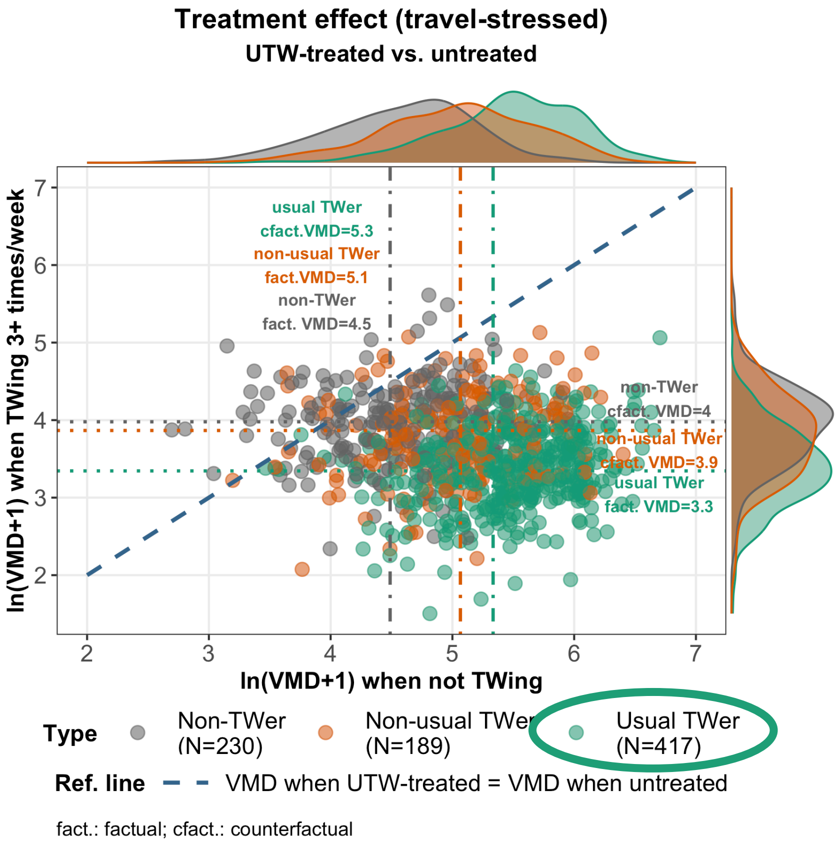
Comparison of both models (travel-stressed and non)

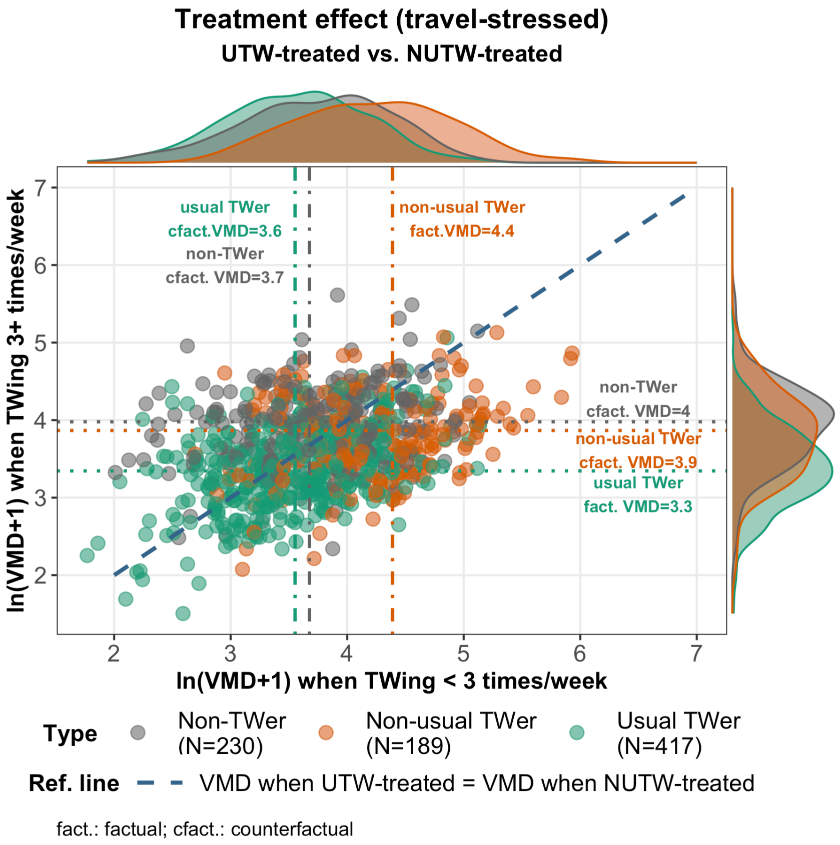




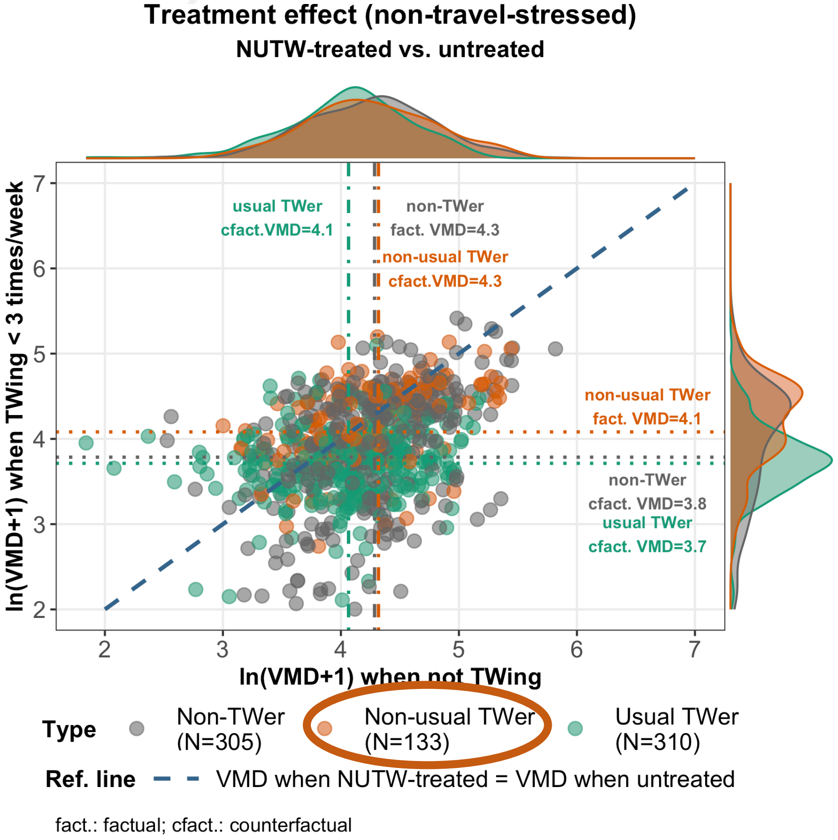
Travel-stressed model (treatments: NUTW & UTW)

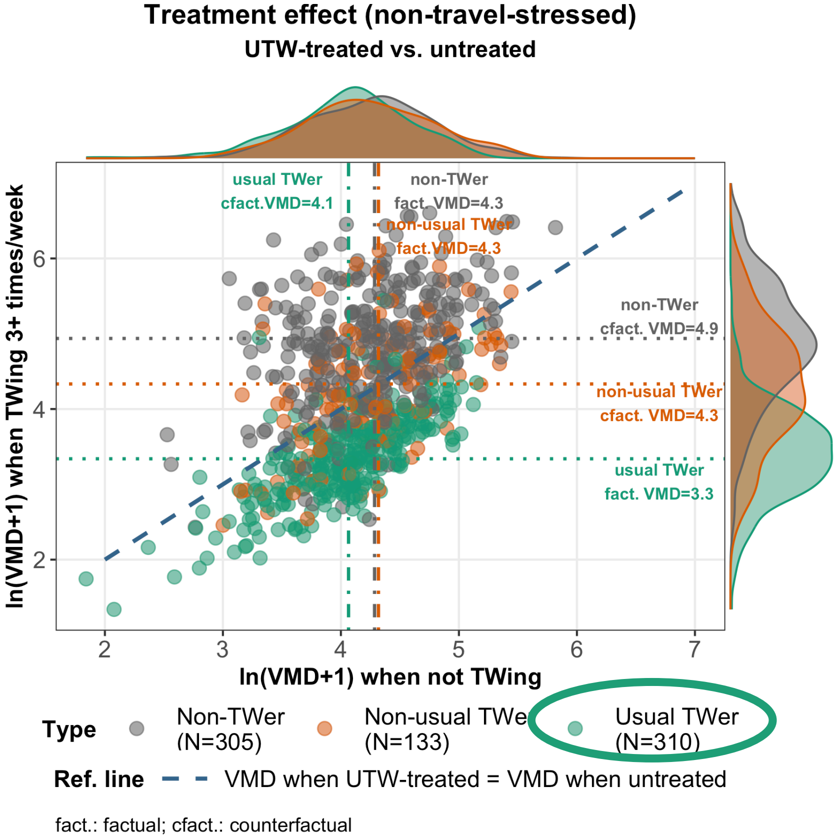


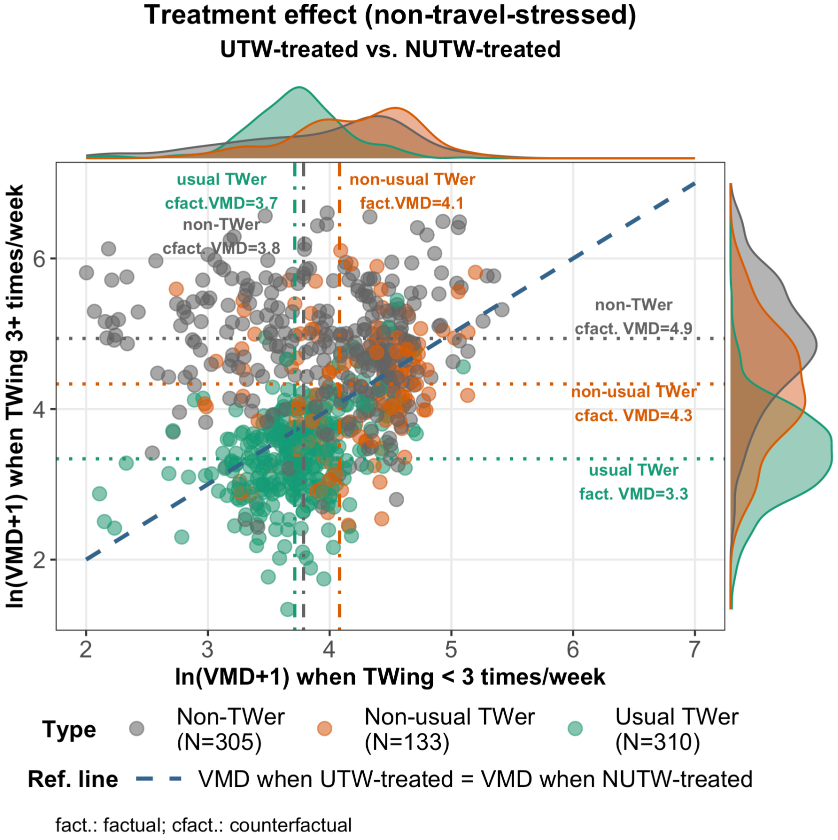




Non-travel-stressed model (treatments: NUTW & UTW)







Georgia Tech

Conclusions (1)

- This study quantifies and compares the impact of **teleworking** on **vehicle-miles driven (VMD)** for different types of teleworkers
  - By teleworking **frequency categories**: non-TWer, non-usual TWer, usual TWer
  - By teleworking-related **motive**: travel-stressed or not
- In all models, **TWing reduced VMD** on average, for its adopters
  - So the cross-sectional results *can* be consistent with the longitudinal ones, when sample selection is accounted for
- TWing reduced VMD ***most for travel-stressed TWers*** (53% of the sample)
- A non-trivial number of **non-travel-stressed non-usual TWers increased VMD** after beginning to TW

Georgia Tech

Conclusions (2)

- What should we do when we suspect a **mismatch** between the **outcome variable** we are interested in, and the **returns (benefit)** the respondent is interested in?
- Assuming the model shows even one significant correlation of error terms, we still have a selection bias to correct!
  - So we should still use the endogenous switching approach
- However, awareness of this issue may
  - Help explain some counterintuitive results
  - Point to a segmentation or respecification that would be more meaningful

Next steps

- **Back-transform** ln(VMD+1) to the raw scale, i.e., VMD
  - May not have a neat analytical expression as is the case for the classic binary probit ESRM (Yen & Rosinski, 2008)
  - Thus, we expect to apply numerical integration
- Develop **ordinal probit switching regression models**
  - Aligning with the ordinal nature of teleworking frequency categories

Thank you!

patmokh@gatech.edu

xinyi.wang@gatech.edu

Acknowledgement:

The study is funded by the private transport company **Cintra,** as an independent research investigation. Any opinions, findings, and conclusions or recommendations expressed in this study are those of the authors and do not necessarily reflect the views of the sponsor organization.

Georgia Tech

References

- **Dubin JA** (1982) *Economic Theory and Estimation of the Demand for Consumer Durable Goods and Their Utilization: Appliance Choice and the Demand for Electricity*. Massachusetts Institute of Technology Energy Laboratory Discussion Paper No. 23, MIT-EL 82-035WP, and PhD Dissertation, Department of Economics.
- **Dubin JA & DL McFadden** (1984) An econometric analysis of residential electric appliance holdings and consumption. *Econometrica* **52(2)**, 345-362.
- **He S & L Hu** (2015) Telecommuting, income, and out-of-home activities. *Travel Behaviour and Society* 2(3), 131-147.
- **Heckman J, JL Tobias, & E Vytlacil** (2001) Four Parameters of Interest in the Evaluation of Social Programs. *Southern Economic Journal* 68(2), 211-223.
- **Kim SN, S Choo, & PL Mokhtarian** (2015) Home-based telecommuting and intra-household interactions in work and non-work travel: A seemingly unrelated censored regression approach. *Transportation Research A* 80, 197-214.
- **Kim SH & PL Mokhtarian** (2022) A note on the sample selection (switching regression) model and treatment effects for a log-transformed outcome variable, in the context of residential self-selection. Under review, available from the authors.
- **Mokhtarian PL, SL Handy, & I Salomon** (1995) Methodological issues in the estimation of the travel, energy, and air quality impacts of telecommuting. *Transportation Research A* 29(4), 283-302.
- **Nakosteen, RA & M Zimmer** (1980) Migration and Income: The Question of Self-Selection. *Southern Economic Journal* **46(3)**, 840-851.
- **Wang, X, SH Kim, & PL Mokhtarian** (2022) Identifying teleworking-related motives and comparing telework frequency expectations in the post-pandemic world: a latent class modeling approach. Paper # TRBAM-S-22-02508 under review for presentation at the Annual Meeting of the Transportation Research Board, January 2023. Available from the authors.
- **Yen ST, and J Rosinski** (2008) On the marginal effects of variables in the log-transformed sample selection models. *Economics Letters* **100(1)**, 4-8.
- **Zhu P** (2013) Telecommuting, household commute and location choice. *Urban Studies* 50(12), 2441-2459.
- **Zhu P & SG Mason** (2014) The impact of telecommuting on personal vehicle usage and environmental sustainability. *International Journal of Environmental Science and Technology* 11(8), 2185-2200.

Georgia Tech