Is teleworking always a “treatment” for reducing distance traveled? Investigating the roles of telework motivations and frequency using multinomial switching regression models

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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.

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

<table>
<thead>
<tr>
<th>Post-COVID changes</th>
<th>vehicle-miles</th>
<th>vehicle-trips</th>
</tr>
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<tbody>
<tr>
<td>More WFH</td>
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<tr>
<td>Impact on nonwork travel?</td>
<td>?</td>
<td>?</td>
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<tr>
<td>Longer commute distances</td>
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<tr>
<td>Higher vehicle ownership</td>
<td>↑</td>
<td>↑</td>
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<tr>
<td>Lower transit share</td>
<td>↑</td>
<td>↑</td>
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<tr>
<td>More long-distance auto travel?</td>
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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*
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

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

Because of this skewed distribution, we log-transformed VMD → \( \ln(VMD+1) \) to improve normality.
A tale of two types of travel diary studies of TWing

<table>
<thead>
<tr>
<th>TW program evaluations</th>
<th>General travel surveys</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small, unrepresentative samples</td>
<td>Large, representative samples</td>
</tr>
<tr>
<td>Focused on TWing</td>
<td>No emphasis on TWing</td>
</tr>
<tr>
<td>Panel data (before-after)</td>
<td>Cross-sectional data</td>
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<tr>
<td>Found travel reductions (TW decreased travel)</td>
<td>Finding complementarity (TW increases travel)</td>
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</table>

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
Longitudinal v. cross-sectional inference

in cross-sectional studies, we need the missing counterfactual

longitudinal estimate of impact

\[ Y_{1\,TW} - Y_{0\,TW} \] (reduction)

\[ Y_{0\,TW} \approx Y_{1\,NTW} \]
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
Key components of a *binary selection* ESRM

- **A selection model** (binary probit):
  - *Telework adoption propensity* = $Wy + \varepsilon$
  - $W$ = explanatory variables, $y$ = coefficients, $\varepsilon$ = error term

- **Two outcome models** (linear regressions):
  - If teleworking ("treated"): $\ln(VMD + 1) = X\beta_1 + \eta_1$
  - If not teleworking ("untreated"): $\ln(VMD + 1) = X\beta_2 + \eta_2$
  - $X$ = explanatory variables, $\beta_1, \beta_2$ = coefficients, $\eta_1, \eta_2$ = error terms

- **Trivariate normal assumption** for the error term distribution:
  $$\begin{bmatrix} \varepsilon \\ \eta_1 \\ \eta_2 \end{bmatrix} \sim N \left( \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho_1 \sigma_1 & \rho_2 \sigma_2 \\ \rho_1 \sigma_1 & \sigma_1^2 & 0 \\ \rho_2 \sigma_2 & 0 & \sigma_2^2 \end{bmatrix} \right)$$
Multinomial logit switching regression (MNLSR) model

• A selection model (multinomial logit, MNL):
  • Probability of TWing category $t$ being selected:
    \[ p^t = P \left( U_t \geq \max_{t' \in T, t' \neq t} U_{t'} \right) = \frac{e^{V_t}}{\sum_{t' \in T} e^{V_{t'}}} \]
    
    \[ U_t = V_t + \varepsilon_t = W\gamma_t + \varepsilon_t, \quad t, t' \in T = \{N, NU, U\} \]
    
    \[ W = \text{explanatory variables, } \gamma_t = \text{coefficients, } \varepsilon_t \sim \text{i.i.d. } \text{Gumbel} \left(0, \frac{\lambda^2}{2}\right) \]

• An integrated outcome model with group-specific coefficients (linear regression):
  \[ \ln(VMD + 1) = 1_N(t) \cdot X_N \beta_N + 1_{NU}(t) \cdot X_{NU} \beta_{NU} + 1_U(t) \cdot X_U \beta_U + \eta \]
  
    \[ X_N, X_{NU}, X_U = \text{explanatory variables, } \beta_N, \beta_{NU}, \beta_U = \text{coefficients, } \eta \sim N(0, \sigma^2) \]

• Connecting the selection and outcome models:
  \[ \mathbb{E}[\eta \mid t] = \sum_{t' \in T} \alpha^{t'} \cdot \frac{p^{t'}}{1 - p^{t'}} \ln P^{t'} - \alpha^t \cdot \ln P^t \]
  
    \[ \alpha^{t'} \text{ is the scaled correlation between } \eta \text{ and } \varepsilon_{t'} \]

Dubin & McFadden 1984; Dubin 1982
Calculation of treatment effects (TEs)

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Observed untreated group: NTWer</th>
<th>Observed NUTW-treated group: NUTWer</th>
<th>Observed UTW-treated group: UTWer</th>
</tr>
</thead>
<tbody>
<tr>
<td>A: If untreated (i.e., if a NTWer)</td>
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<tr>
<td>B: If NUTW-treated (i.e., if a NUTWer)</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>C: If UTW-treated (i.e., if a UTWer)</td>
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\[ \text{B-A: NUTW-TE on the untreated} \]
\[ \text{C-A: UTW-TE on the untreated} \]

\[ \text{C-B: UTW- and NUTW-TE diff. on the untreated} \]

\( \text{fact.} = \text{factual} \)
\( \text{cfact.} = \text{counterfactual} \)
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)
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)
Comparison of both models (travel-stressed and non)

**Treatment effect summary (travel-stressed)**

- **Type**
  - Non-TW (N=230)
  - Non-usual TW (N=189)
  - Usual TW (N=417)

**Treatment effect summary (non-travel-stressed)**

- **Type**
  - Non-TW (N=305)
  - Non-usual TW (N=133)
  - Usual TW (N=310)
Travel-stressed model (treatments: NUTW & UTW)

- Treatment effect (travel-stressed)
  - NUTW-treated vs. untreated
  - UTW-treated vs. untreated
  - UTW-treated vs. NUTW-treated

**Graphs:**
- In(VMD+1) when TWing < 3 times/week
- In(VMD+1) when not TWing
- Ref. line: VMD when NUTW-treated = VMD when untreated
  - fact.: factual; cfact.: counterfactual

**Legend:**
- Non-TWer (N=230)
- Non-usual TWer (N=189)
- Usual TWer (N=417)
Non-travel-stressed model (treatments: NUTW & UTW)
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.
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!

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References