Estimating the effects of hybrid and remote work on weekly vehicle miles traveled

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  - **Displacement effect**: Existing trips can be *shifted* between in-person and remote days, thus *displacing* VMT (rather than creating new VMT).
- To that end, we need to understand how VMT changes *over the course of a week* to account for rebound and displacement effects.

Example: Three Friends in a Simple City

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Day	Activity Pattern	Daily VMT
Sunday (No Work)	*None*	0
Monday (In Office)	Home to Work (10), Work to Grocery Store (12), Grocery Store to Home (2)	24
Tuesday (In Office)	Home to Work (10), Work to Home (10)	20
Wednesday (In Office)	Home to Work (10), Work to Home (10)	20
Thursday (In Office)	Home to Work (10), Work to Grocery Store (12), Grocery Store to Home (2)	24
Friday (In Office)	Home to Work (10), Work to Home (10)	20
Saturday (No Work)	*None*	0
Weekly Total		**108**

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Day	Activity Pattern	Daily VMT
Sunday (No Work)	*None*	0
Monday (Remote)	Home to Gym (2), Gym to Grocery Store (2), Grocery Store to Home (2)	6
Tuesday (In Office)	Home to Work (10), Work to Home (10)	20
Wednesday (In Office)	Home to Work (10), Work to Home (10)	20
Thursday (In Office)	Home to Work (10), Work to Home (10)	20
Friday (Remote)	*Work from home only*	0
Saturday (No Work)	Home to Gym (2), Gym to Grocery Store (2), Grocery Store to Home (2)	6
Weekly Total		**72**

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Day	Activity Pattern	Daily VMT
Sunday (No Work)	*None*	0
Monday (Remote)	Home to Gym (2), Gym to Grocery Store (2), Grocery Store to Home (2)	6
Tuesday (Remote)	*Work from home only*	0
Wednesday (Remote)	Home to Gym (2), Gym to Home (2)	4
Thursday (Remote)	*Work from home only*	0
Friday (Remote)	Home to Gym (2), Gym to Grocery Store (2), Grocery Store to Home (2)	6
Saturday (No Work)	*None*	0
Weekly Total		**16**

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  - Travel behavior can be analyzed pre-COVID and post-COVID.
  - Since it's a week-long survey, we can capture how VMT rebounds (and possibly is displaced) as a result of different work arrangements.
- Who's in the final survey for analysis?
  - People with 7 days' worth of data.
  - No students, no people who drive *for* work (i.e. delivery drivers), no people on vacation.
- **3,266 people** making **131,255 trips**

Research Questions

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2. What are the factors that influence someone being an always in-person, hybrid, or always remote worker?
3. By what percentage does additional non-work VMT change as a result of a given work arrangement (**rebound effect**)?
4. How is non-work travel displaced as a result of a given work arrangement (**displacement effect**)?

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- Phase 1: Exploratory data analysis.
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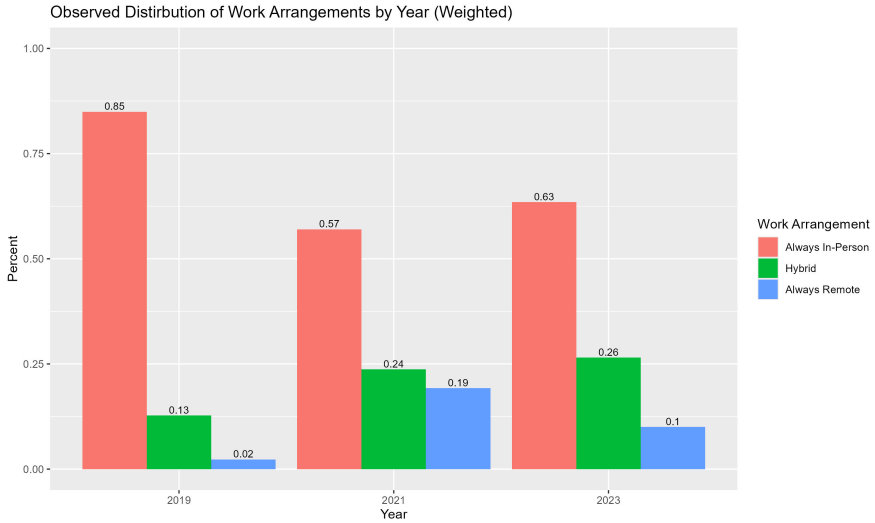
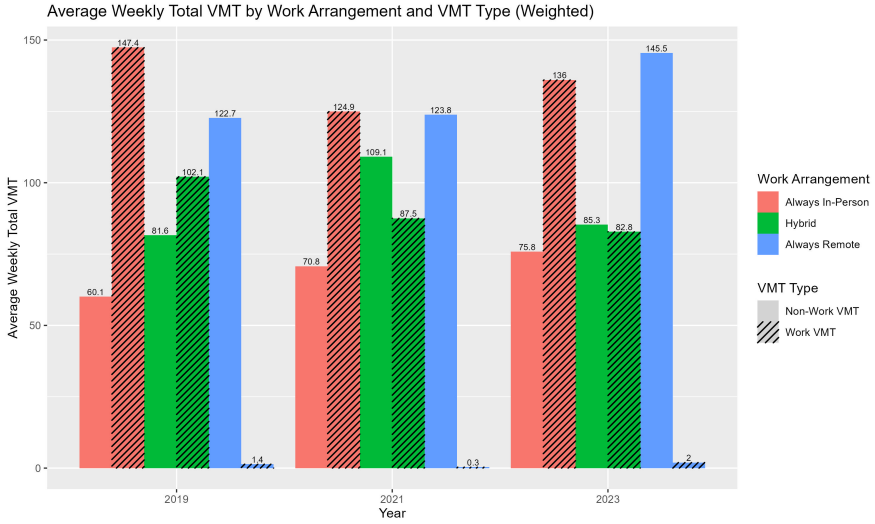
- Phase 3: Representation in a travel demand model.

Always in-person work has decreased since 2019, and hybrid/always remote work have increased.



Always remote and hybrid workers have higher weekly non-work VMT than always in-person workers.



But the increase in non-work VMT from always remote and hybrid workers doesn't necessarily offset the savings in work VMT.

Work Arrangement	Weekly Total VMT Pct. Change (Relative to Always In-Person)	Weekly Work VMT Pct. Change (Relative to Always In-Person)	Weekly Non-Work VMT Pct. Change (Relative to Always In-Person)
Always Remote	-36%	-99%	102%
Hybrid	-13%	-36%	37%

An ordinary least squares (OLS) regression model can control for other factors that affect weekly VMT.

- $ln(WeeklyVMT_i) = \alpha + \beta_1 ObesrvedWorkArrangement_i + \beta_2 \mathbf{S_i} + \beta_3 \mathbf{H_i} + \beta_4 \mathbf{B_i} + \beta_5 Year + \varepsilon$

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  - $\mathbf{S_i}$ is a vector of socioeconomic covariates (age group, gender, employment level, race) for respondent i.
  - $\mathbf{H_i}$ is a vector of household characteristics (household income, number of kids, number of vehicles, number of other hybrid or remote employees in the same home)
  - $\mathbf{B_i}$ are measures of the built environment (jobs per household, employment entropy, intersection density, jobs within 30 minutes of transit).
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- Moreover, there are unobservable factors that influence work arrangement that also affect weekly VMT (e.g. being a homebody, desire for work/life balance, etc.).
- **Ordered probit switching regression (OPSR)** addresses both of these concerns.[1]

[1] Wang and Mokhtarian (2024), Heimgartner and Wang (2024).

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Accounting for selection on unobservables reduces the effect of hybrid/remote work on weekly VMT (compared to other methods).

Specification	Pct. difference in weekly VMT for always remote workers (relative to always in-person)	Pct. difference in weekly VMT for hybrid workers (relative to always in-person)
Difference in means	-36%	-13%
OLS Model	-40%	-9%
OPSR Model	-29%	-6%

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  - Compare percentage differences in mean VMTs by work arrangement between ActivitySim and results from statistical models.
- More broadly, this could be useful for modelers working with jurisdictions that have VMT reduction goals (e.g. California, Colorado, Minnesota).

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  - Try more specifications for the OPSR models.
- **Main takeaway:** utilizing a week-long survey gets us closer to modeling the true effects of hybrid and remote-work on VMT.

Appendix A: OLS Model Estimation Results

	ln_weekly_vmt
work_arrAlways Remote	-0.503*** (0.083)
work_arrHybrid	-0.092** (0.037)
age_group18 to 34	0.049** (0.023)
age_group55 or older	-0.068** (0.029)
genderMale	0.047* (0.026)
employmentEmployed part-time	-0.105*** (0.030)
employmentSelf-employed	0.047 (0.088)
racenonWhite	-0.130*** (0.025)
50K	0.036 (0.033)
150K	0.039 (0.027)
200K	-0.008 (0.032)
200K+	0.018 (0.035)
income_detailedUndisclosed	0.040 (0.040)
num_kids1+ kid	-0.124*** (0.028)
educationno_bach_plus	0.020 (0.021)
num_vehicles1 vehicle	1.511*** (0.187)
num_vehicles2+ vehicles	1.563*** (0.187)
num_hybrid_or_remote	-0.077** (0.037)
jobs_per_hh	0.006** (0.003)
emp8_ent	0.009 (0.048)
intersection_den	-0.002*** (0.0002)
transit_jobs30	-0.00000*** (0.00000)
survey_year2021	-0.043 (0.033)
survey_year2023	-0.002 (0.026)
work_arrAlways Remote:survey_year2021	0.019 (0.103)
work_arrHybrid:survey_year2021	0.071 (0.065)
work_arrAlways Remote:survey_year2023	0.151 (0.103)
work_arrHybrid:survey_year2023	-0.049 (0.056)
genderMale:num_kids1+ kid	0.097*** (0.037)
Constant	3.803*** (0.191)
Observations	3,266
R2	0.147
Adjusted R2	0.140
Residual Std. Error	8.713 (df = 3236)
F Statistic	19.279*** (df = 29; 3236)
Note:	*p<0.1; **p<0.05; ***p<0.01

Appendix B: OPSR Model Estimation Results (Weekly VMT)

	Model 1
kappa1	1.110 (0.074) ***
kappa2	2.024 (0.080) ***
sigma1	0.535 (0.010) ***
sigma2	0.521 (0.061) ***
sigma3	0.558 (0.060) ***
rho1	-0.074 (0.115)
rho2	0.304 (0.368)
rho3	0.385 (0.290)
s_hh_income_under50	-0.290 (0.112) **
s_hh_income100to150	0.151 (0.089)
s_hh_income150to200	0.348 (0.101) ***
s_hh_income_200plus	0.530 (0.082) ***
s_hh_income_undisclosed	0.127 (0.146)
s_no_bach_plus	-0.266 (0.063) ***
s_employed_part_time	-0.180 (0.091) *
s_self_employed	0.778 (0.118) ***
s_year2021	0.865 (0.065) ***
s_year2023	0.742 (0.064) ***
s_self_employed:year2021	0.034 (0.239)

o1_(Intercept)	4.436 (0.291) ***
o1_employed_part_time	-0.078 (0.037) *
o1_self_employed	0.129 (0.079)
o1_male	0.109 (0.022) ***
o1_age18to34	0.004 (0.027)
o1_age55plus	-0.113 (0.032) ***
o1_kids_1plus	-0.112 (0.026) ***
o1_nonwhite	-0.079 (0.035) *
o1_vehicle1	0.876 (0.288) **
o1_vehicle2plus	0.957 (0.286) ***
o1_jobs_per_hh	-0.000 (0.002)
o1_intersection_den	-0.002 (0.000) ***
o1_emp8_ent	-0.058 (0.059)
o1_year2021	0.090 (0.057)
o1_year2023	0.009 (0.040)
o1_self_employed:year2021	-0.260 (0.153)
o1_vehicle2plus:year2021	-0.139 (0.064) *

o2_(Intercept)	5.166 (0.323) ***
o2_no_bach_plus	-0.069 (0.086)
o2_employed_part_time	-0.046 (0.085)
o2_self_employed	0.054 (0.170)
o2_jobs_per_hh	-0.011 (0.008)
o2_intersection_den	-0.002 (0.000) ***
o2_emp8_ent	0.064 (0.117)
o2_remote_day_pct	-0.470 (0.116) ***
o2_year2021	0.193 (0.152)
o2_year2023	0.091 (0.166)
o2_self_employed:year2021	0.405 (0.239)
o2_year2021:vehicle2plus	-0.110 (0.105)
o3_(Intercept)	4.322 (0.410) ***
o3_hh_income_under50	-0.071 (0.214)
o3_hh_income100to150	0.139 (0.123)
o3_hh_income150to200	0.110 (0.137)
o3_hh_income_200plus	0.118 (0.136)
o3_hh_income_undisclosed	0.321 (0.176)
o3_male	-0.170 (0.079) *
o3_jobs_per_hh	0.002 (0.007)
o3_intersection_den	-0.000 (0.001)
o3_emp8_ent	0.080 (0.180)
o3_kids_1plus	-0.203 (0.075) **
o3_year2021	0.167 (0.161)
o3_year2023	0.220 (0.146)
o3_year2021:self_employed	0.305 (0.188)
o3_year2021:vehicle2plus	0.023 (0.122)
AIC	9370.620
BIC	9754.374
Log Likelihood	-4622.310
Num. obs.	3266

*** p < 0.001; ** p < 0.01; * p < 0.05

Appendix B: OPSR Model Estimation Results (Weekly VMT)

```
> print(opsr_model1_rep_te)
Treatment Effects

TE

              G1            G2            G3
T1->T2 -0.18342 *** -0.05674 *** -0.18438 ***
T1->T3 -0.90173 *** -0.49210 *** -0.33863 ***
T2->T3 -0.71831 *** -0.43536 *** -0.15426 ***


ATE

   T1->T2      T1->T3      T2->T3
1 -0.1601 *** -0.7869 *** -0.6268 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> ## Average treatment effect on treated (hybrid workers)
> exp(-0.05674) - 1
[1] -0.0551603
> ## Average treatment effect on treated (always remote workers)
> exp(-0.33863) - 1
[1] -0.2872539
```