Stability of travel behavior: Longitudinal data analysis

3rd Symposium on Activity-Based Modeling
Raitenhaslach, 11-13 December 2024

Dr. Rolf Moeckel, Dr. Ana Moreno
Technical University of Munich

DALL-E: pedestrian, bike, train and auto as a pencil drawing

Stability of Travel Behavior

Stability of travel behavior

Travel behavior may differ a lot from day to day (Raux et al. 2016, Hanson 1988, Huff et al. 1986)

Travel behavior is rather stable from year to year (McCarthy 1982, Kitamura 1987, Jones 1988, Cui et al. 2014)

To a large degree, travel behavior is driven by habitual choices that do not change often (Gärling & Axhausen 2003).

Workdays are more stable than non-workdays, travel time is more stable than trips (Schlich & Axhausen 2003)

Source: hhagedorn on https://qimby.net/

Change of travel behavior

Change in travel behavior is typically driven by one (or more) of the following:

Change in levels of service (such as congestion, transit service, bike paths)

1. Change in activity locations (such as a new shopping mall)

1. Policy interventions (Verplanken & Wood 2006)

1. Demographic change (birth of a child, change of income, change of car ownership, household relocation) (Murakami et al. 1992, Schneider 2016, Clarke et al. 2014)

For most households, such changes are **rare**.

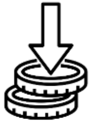
Panel data and travel behavior change

Moreno, A.T., Nouli, G., Ahmed, U., Schiffer, M., Moeckel, R. (2023). Understanding the Impact of Life Events on Travel Behavior Change via Machine Learning. 25th Euro Working Group on Transportation Meeting (EWGT 2023)

Panel survey data

- **German Mobility Panel** data (2010 - 2019):
  - Respondents were asked to participate in **3 consecutive years**
  - Each year, participants provide:
    - A **7-day trip diary**
    - Socio-demographic attributes
    - Mobility resources
  - Raw data: 589,357 trips of **25,449 individuals**

- Data were reduced to obtain:
  - **Active days by purpose**
  - **Life events**



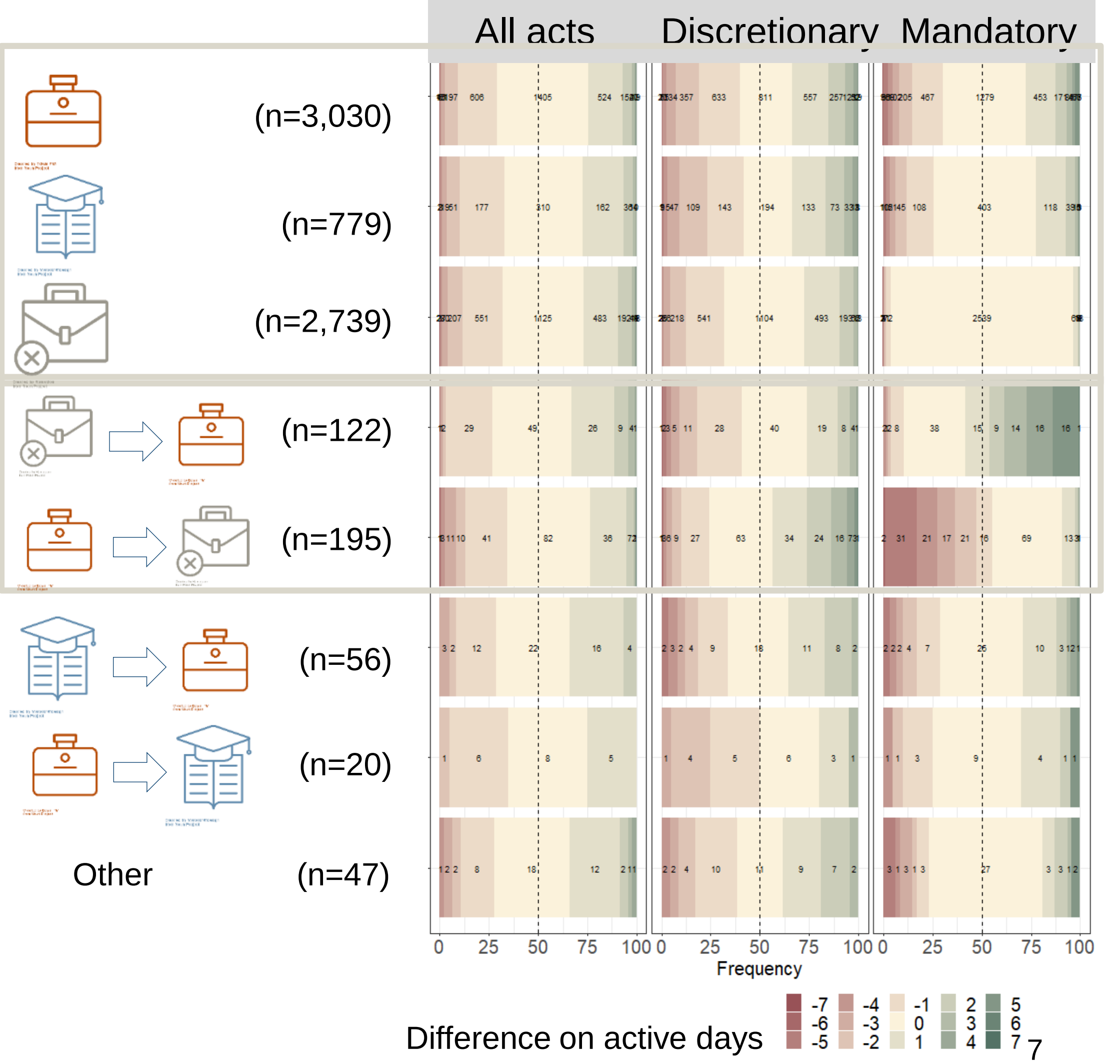



Final sample: **7,074 individual observations**

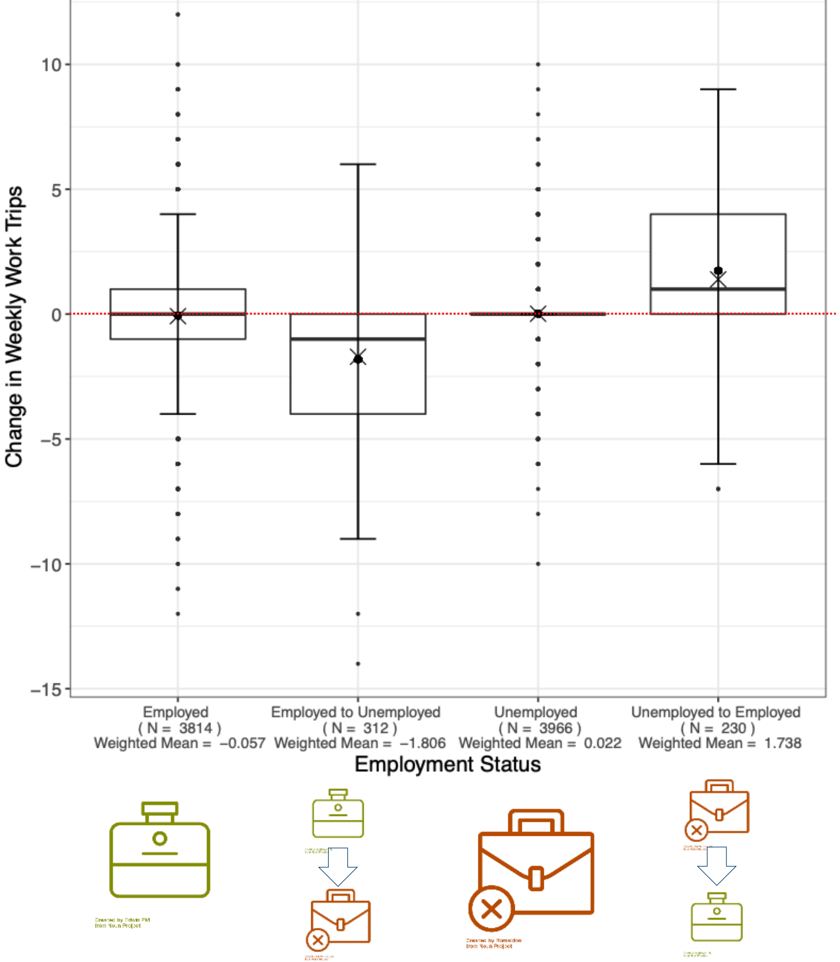
Analysis of life events

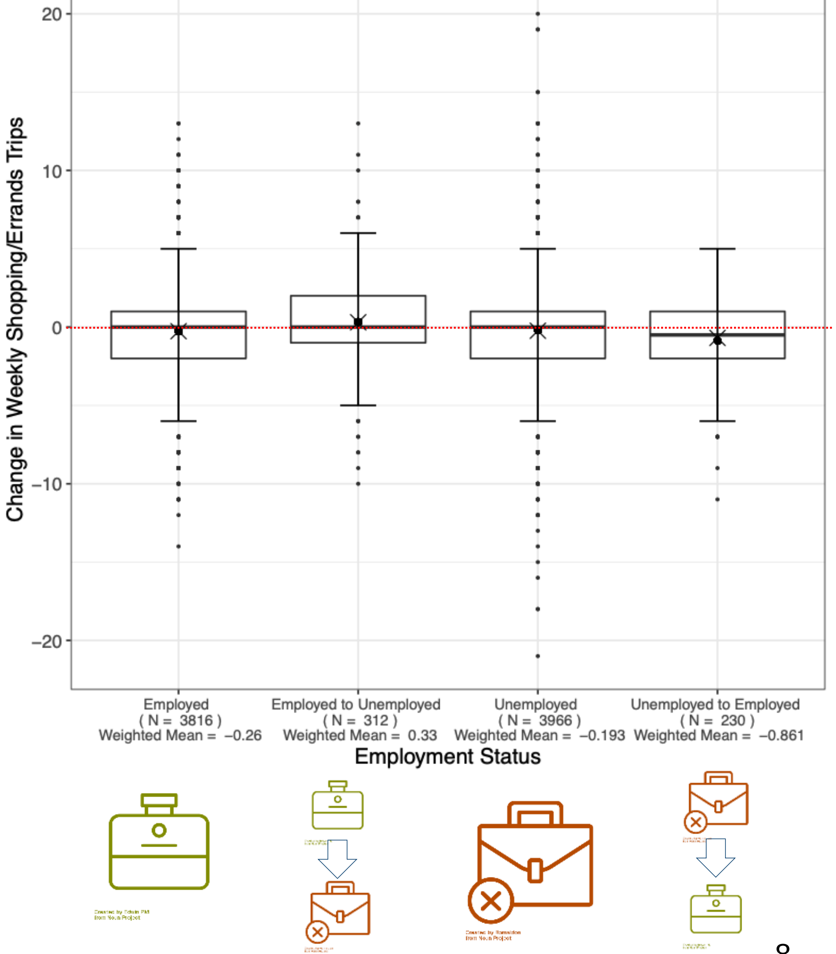
Becoming employed or unemployed trigger the **highest differences** on mandatory active days and slight variations in discretionary active days

Active days are rather **stable for unemployed** (95%), employed (50%) and **students** (60%)



Source: Ahmed & Moeckel (2023)





Methodology

Active days by purpose

Sociodemographics

Life events

Traditional econometric model

Zero-inflated negative binomial model (Hurdle)

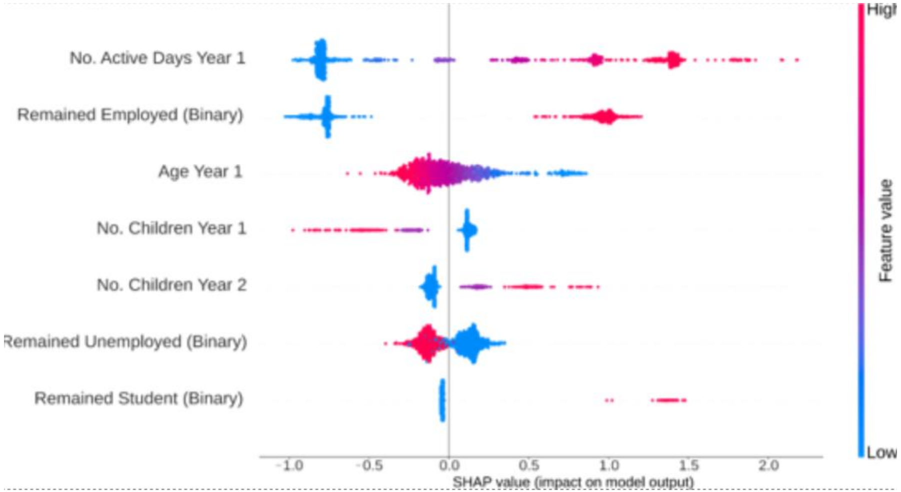
Machine learning pipeline

Stratified four-fold cross-validation on the training set

Machine learning-informed econometric model

Number of active days on the second year

Purpose	Data split	Linear	Lasso	Ridge	KNN	SVR	RFs	MLPs
Mandatory	Training	0.743	0.756	0.756	0.740	0.740	**0.843**	0.751
	Testing	0.767	0.769	0.769	0.754	0.757	**0.776**	0.775



Top 7 features

Purpose	Model	Traditional	ML-informed
Mandatory	Zero-state	0.508	0.536
	Count-state	0.559	0.565
Discretionary	Zero-state	0.472	0.476
	Count-state	0.676	0.677

Pseudo R^2

Mobile Phone Data and Travel Behavior Stability

Moreno, A.T., Alvarez-Ossorio, S., Moeckel, R., Bogenberger, K. (2024). Stability of weekly active days using continuous revealed preference data. 12th Symposium of the European Association for Research in Transportation

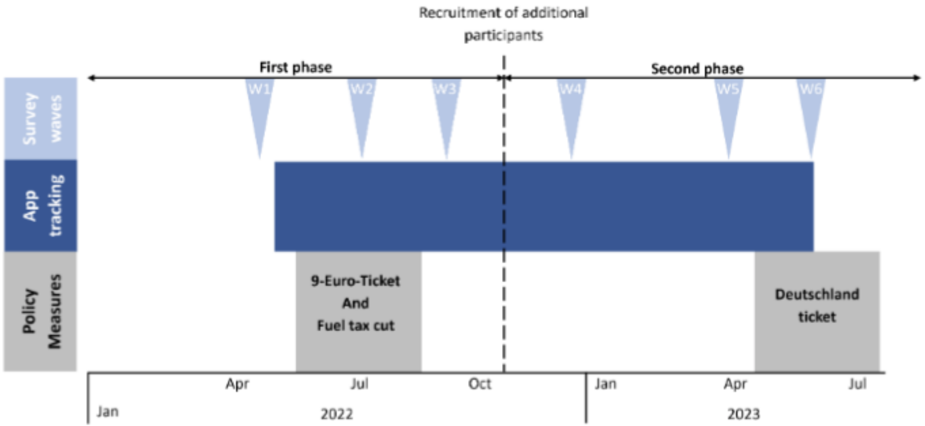
MOBILITÄT LEBEN

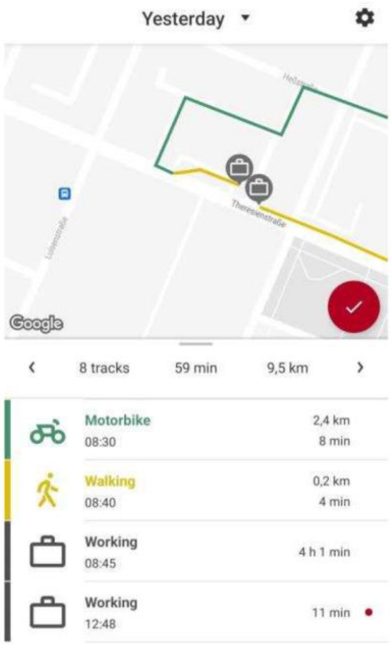
Ein Forschungsprojekt gefördert durch die
Hochschule für Politik München
an der Technischen Universität München

Data

- **Mobilität.Leben** project (2022-2023):
  - Initial objective: analyze the impacts of the 9-euro ticket and fuel-tax cut
  - Multi-wave survey with over 2,500 participants:
    - Over 1,100 also recorded movements with app

Initial sample: **65,360 person-weeks (1,193 persons)**





Research idea

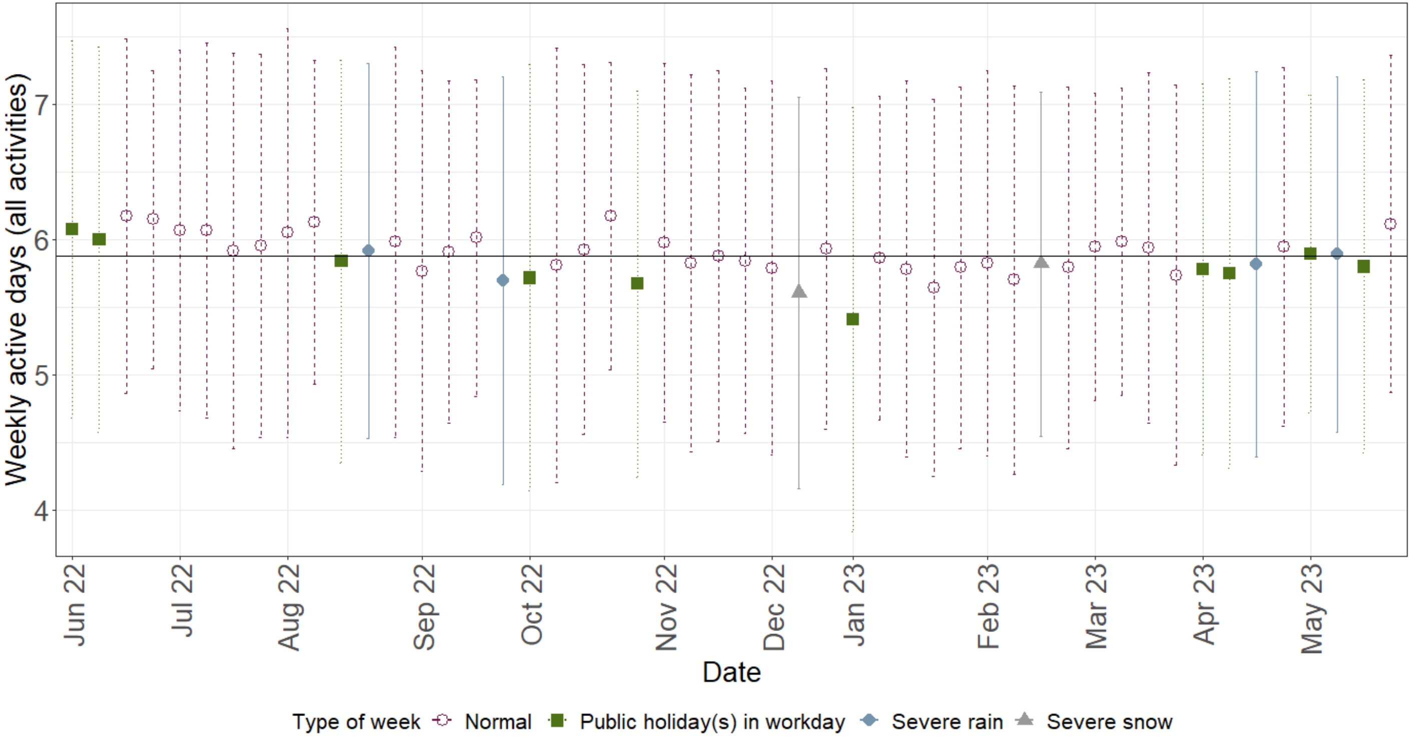
Major strength of data:
Individuals can be traced **over multiple days**

Analyses:

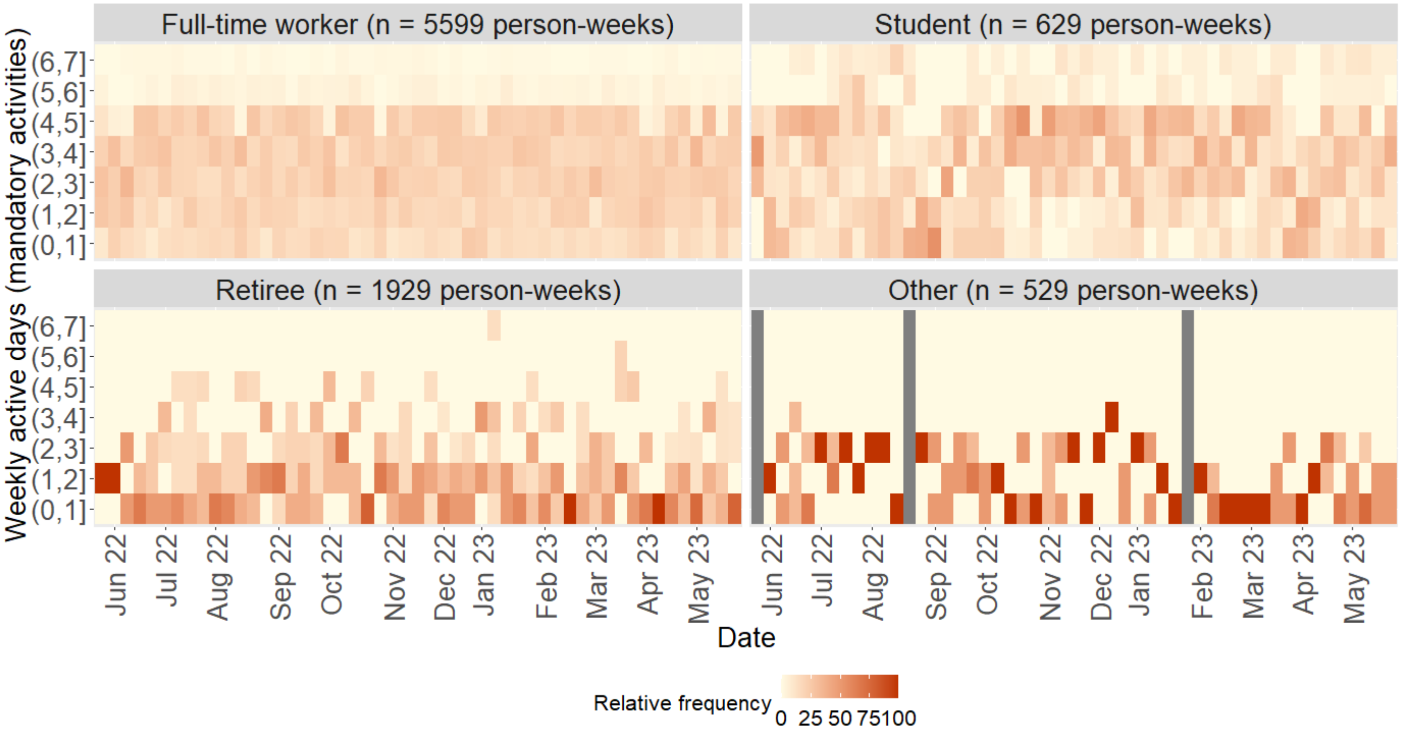
- **How many trips** are made by a participant day after day
- Does the participant repeatedly visit **the same destination**? Several times per day, per week, per month?
- What **time of day** are repeated destinations visited?

Final sample: **10,631 person-weeks (355 persons)** – 16% of initial sample

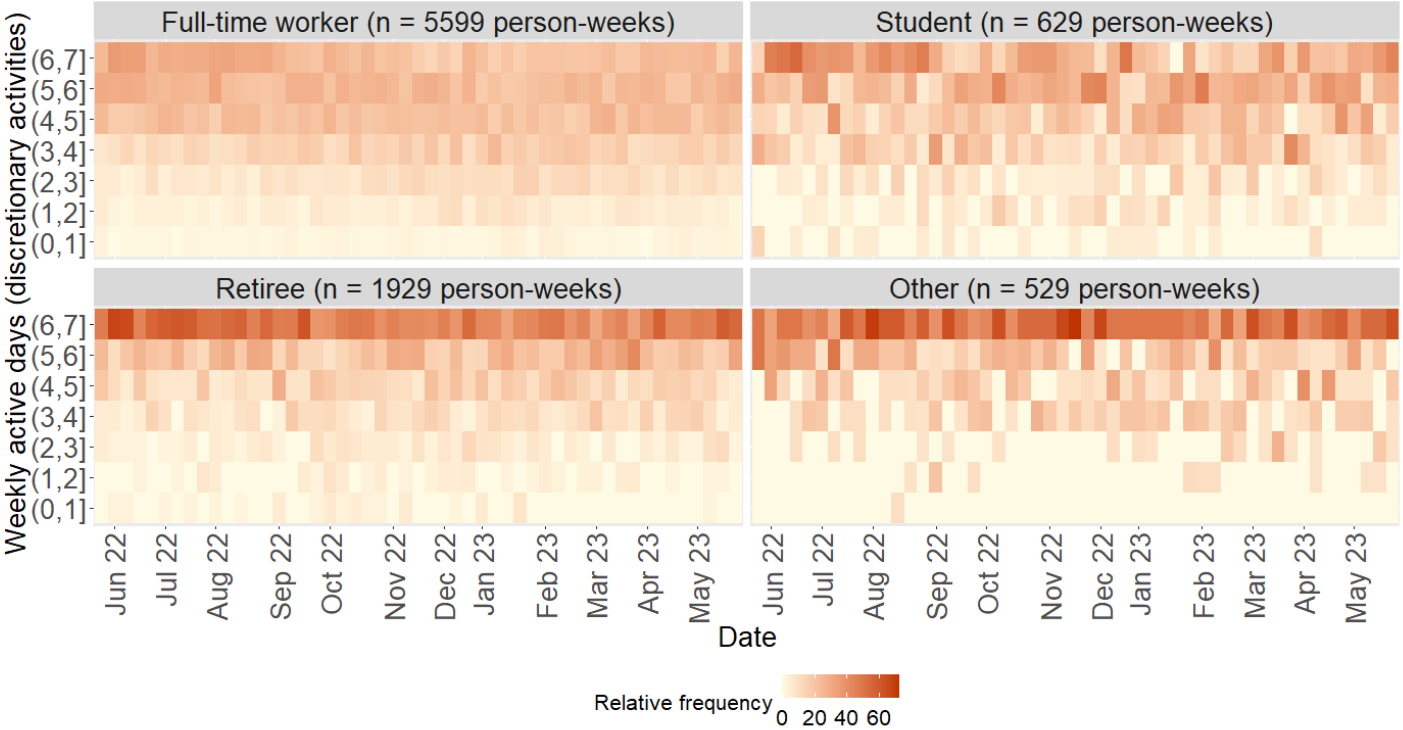
Variation of days per week with out-of-home activities



Annual variation by employment status - mandatory



Annual variation by employment status - discretionary



Effects of life events

	Mandatory	Discretionary	All
Full-time workers who discontinued working	− days	+ variability	
Single person to two-person household			+ days − variability
Increased household income low - medium			+ days − variability
Increased from zero to one auto			− days

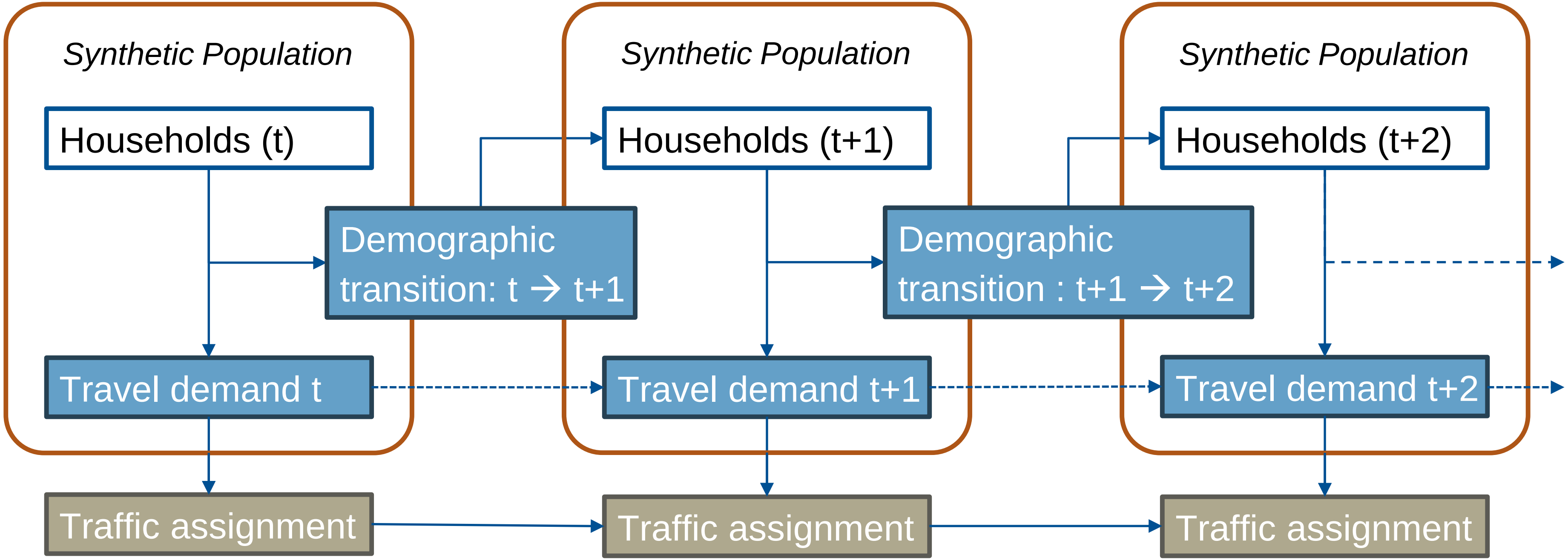
Retirees had a similar number of weekly active days as full-time workers. Semi-passive data could capture underreported short trips

Study Rationale

Research rationale

- Most transport models **recreate travel behavior from scratch** each time the model runs.
- Travel choice are created from scratch every model run, **ignoring habitual behavior**.
- In **land use modeling**, we have long overcome recreating populations from scratch every simulation period (Waddell 2002).
- **The time is now** for transport modeling to catch up with land use modeling.

Model concept



Issues encountered

- Looked into number of trips, active days and mode choice so far.
- Maybe more promising to explore travel times and activity durations: Someone who changes from unemployed to employed might make the same number of activities, but selects activities that are nearer or they may attend activities for shorter time periods. Or even switch to online activities. Or delegate activities to other household members.
- Data collection should focus on activities, not just trips. Time use surveys as panel surveys?
- Might require oversampling segments of the population that are more likely to undergo life events.
- Possibly, we are not collecting the right data?

Data and Theory Requirements

What do we need?

Remove noise of day-to-day randomness and reveal:

Stability of travel behavior over time

Impact of life events on travel behavior

Data requirements

- Only **panel data** can truly capture stability of individual travel behavior versus impacts of life events.
- Given the limited understanding how stable travel choices are, **cross-sectional data** are insufficient to explain individual stability of travel behavior
- Given the apparent randomness in daily travel choices, longer periods need to be captured.

→ Mobile phone data as the next best option?

Main challenge

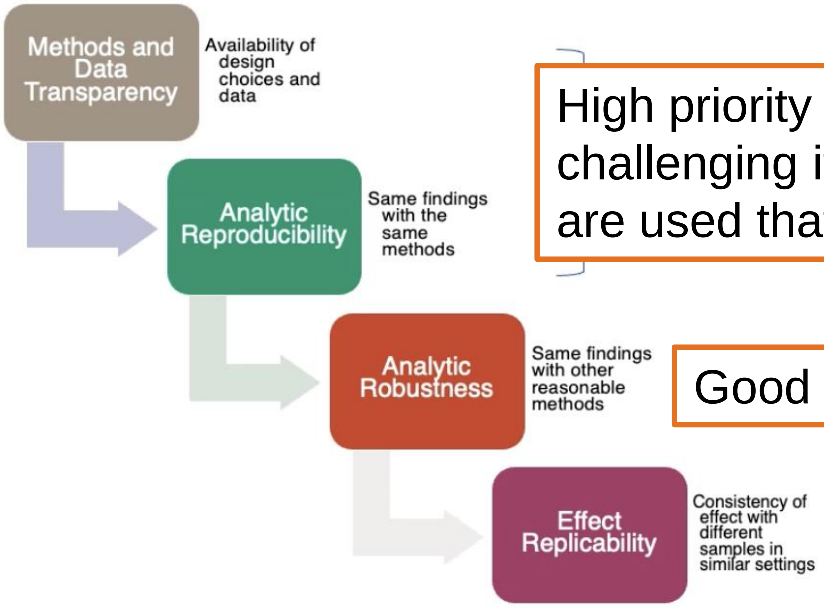
Mobile phone data potential

- Mobile phone data are effortless for the respondent and can be collected over long time periods
- Self-reporting in panel data is error-prone, less so in mobile phone data
- Short trips are underrepresented in survey data, less so in mobile phone data

Mobile phone data challenges

- Needs a lot of cleaning that might influence results
- Tracks based on cell phone towers are very coarse, particularly in rural areas
- It is challenging to collect information on life events

Elements of credibility



High priority for us, but it may be challenging if mobile phone data are used that cannot be shared.

Good idea.

What would this mean?

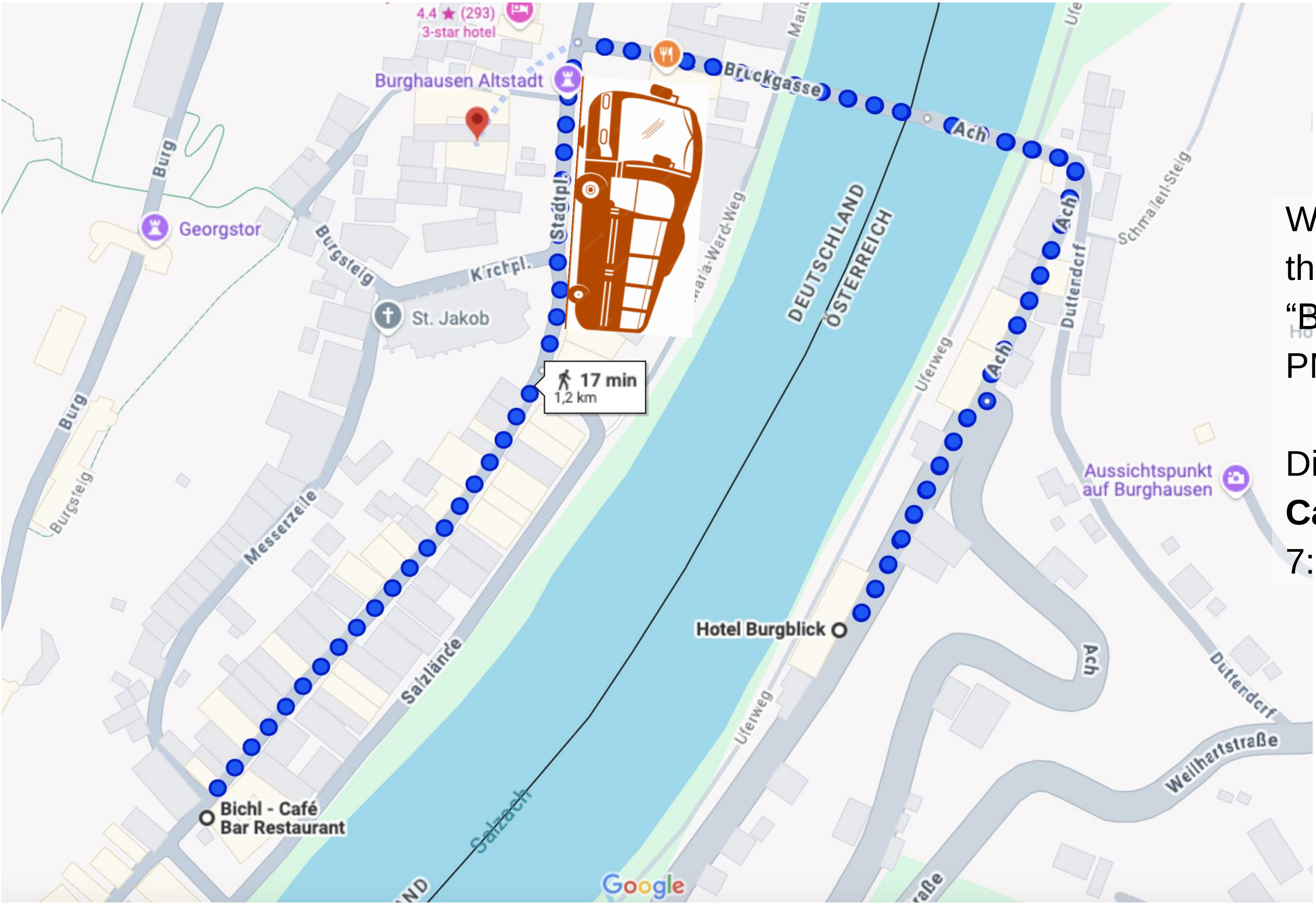
Also important

LeBel EP, McCarthy RJ, Earp BD, Elson M, Vanpaemel W. A Unified Framework to Quantify the Credibility of Scientific Findings. *Advances in Methods and Practices in Psychological Science.* 2018;1(3):389-402.

Conclusions

- **Day-to-day travel behavior variability** cannot be explained by currently observed data.
- Travel behavior **over weeks is rather stable** and should not be reinvented every time the transport model runs.
- Much behavior is **driven by habits** that should **not** be modeled with tabula-rasa methods.
- It is time for **transport modeling** to catch up with **land use modeling** and adjust travel behavior incrementally, rather than reinventing it from scratch every time the model runs.

Photo by Ryoji Iwata on Unsplash



We will leave from the hotel lobby “Burgblick” at 6:45 PM.

Dinner starts at **Café Bichl** at 7:00 PM.

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Data duration

Single day

- Traditional HTS
- Does not capture habitual behavior
- Easier to collect

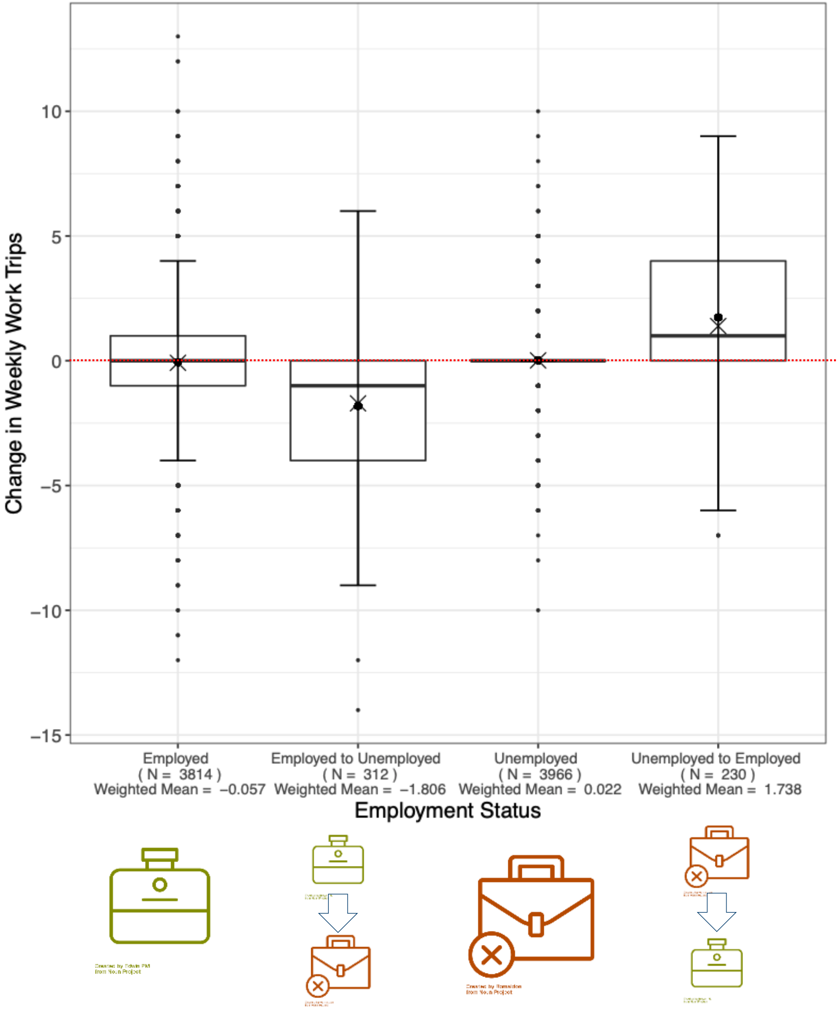
Backup slides

Live events studies

Types:
- change in employment status of a person
- change in household size
- change in household income
- birth of a new child
- change in household car ownership
- household relocation

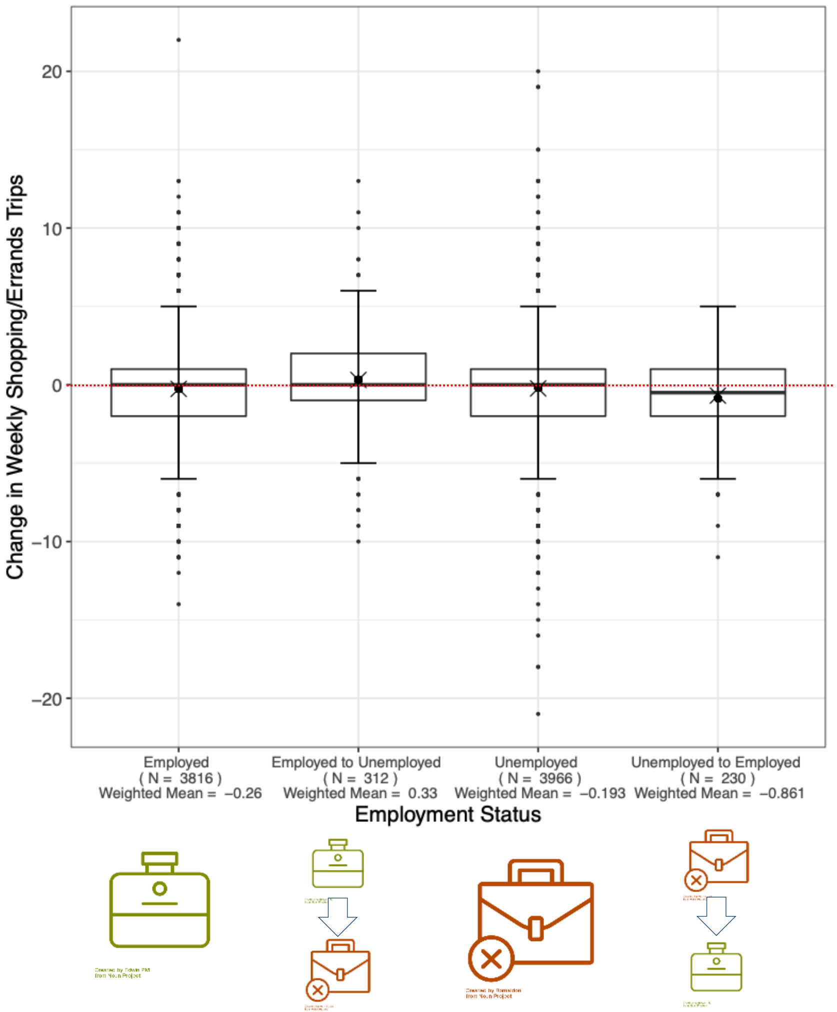
Number of Life Events	Persons	Proportion
0	5,404	54.8%
1	3,275	33.2%
2	876	8.9%
3	237	2.4%
4	56	0.6%
5	9	0.1%
6	2	0.0%

Source: Ahmed & Moeckel (2023)



Change in weekly work trips due to change in employment

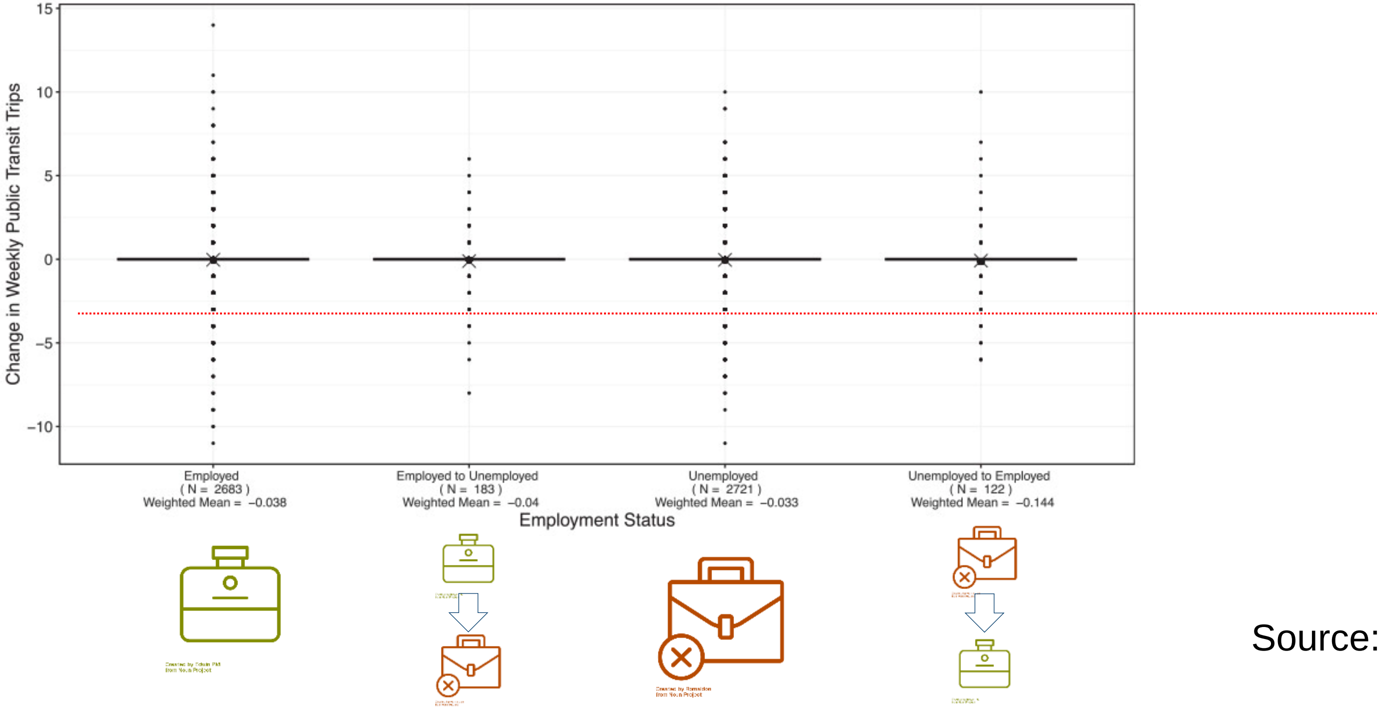
Source: Ahmed & Moeckel (2023)



Change in weekly shopping trips due to change in employment

Source: Ahmed & Moeckel (2023)

No explanatory power for number of transit trips



Source: Ahmed & Moeckel (2023)

Sample size MOP

Event	All		Females		Males	
	Count	Frequency	Count	Frequency	Count	Frequency
Household changes						
change.hh.size	507	6.57	271	6.57	236	6.56
change.hh.adults	708	9.17	380	9.21	328	9.12
change.hh.children	446	5.78	235	5.70	211	5.87
change.hh.cars	686	8.88	371	9.00	315	8.76
change.hh.urban	147	1.90	86	2.09	61	1.70
change.hh.income	2,957	38.30	1,558	37.78	1,399	38.89
change.hh.econStatus	1,568	20.31	831	20.15	737	20.49
change.hh.regionType	36	0.47	21	0.51	15	0.42
change.hh.municipalityType	142	1.84	76	1.84	66	1.83

Sample size MOP

Event	All		Females		Males	
	Count	Frequency	Count	Frequency	Count	Frequency
Person changes						
change.p.age_gr	580	7.51	308	7.47	272	7.56
change.p.female	3	0.04	1	0.02	2	0.06
change.p.driversLicense	311	4.03	201	4.87	110	3.06
change.p.ownBicycle	935	12.11	504	12.22	431	11.98
change.occMob	1,117	14.47	646	15.66	471	13.09
change.p.occupationStatus	665	8.61	412	9.99	253	7.03
change.p.seasonTicket	1,250	16.19	702	17.02	548	15.23
change.p.mobilityRestriction	484	6.27	256	6.21	228	6.34
change.p.change.workplace	1,295	16.77	718	17.41	577	16.04
change.p.workplace.areaType	1,079	13.97	589	14.28	490	13.62
change.p.workplace.parking	1,303	16.88	737	17.87	566	15.74
change.hh.structure	474	6.14	256	6.21	218	6.06

Sample size MOP

Event	All		Females		Males	
	Count	Frequency	Count	Frequency	Count	Frequency
Dwelling changes						
change.hh.bus5minWalk	1,143	14.80	639	15.49	504	14.01
change.hh.bus10minWalk	457	5.92	262	6.35	195	5.42
change.hh.rail10minWalk	450	5.83	231	5.60	219	6.09
change.hh.rail15minWalk	512	6.63	288	6.98	224	6.23
change.hh.rail20minWalk	614	7.95	316	7.66	298	8.28
change.hh.homePT	4,041	52.34	2,167	52.55	1,874	52.10
change.hh.singleParent	32	0.41	17	0.41	15	0.42
change.hh.childrenUnder10	460	5.96	247	5.99	213	5.92
change.hh.relocation	0	0.00	0	0.00	0	0.00
change.hh.parking	429	5.56	227	5.50	202	5.62
change.hh.putSatisfaction	1,236	16.01	654	15.86	582	16.18
change.hh.firstChildBirth	187	2.42	98	2.38	89	2.47

Conclusions from machine learning

- Structural insights from the explainable **machine learning** pipeline allowed to **improve traditional model predictions**
- **Active days** are rather **stable** across time, being mandatory acts more stable than discretionary acts
- The results show the **gendered effects of giving birth** on change in mandatory and discretionary active days. **Employment change** also played a key role on mandatory active days
- Future work will use the machine learning pipeline to inform traditional model estimation for other travel variables, such as traveled distance, mode choice, or vehicle ownership

Source: Moreno et al. (2024)

Methodology: machine learning pipeline

Data split

1. Training (80%) and testing (20%)
2. Stratified random split
3. Strata based on the distribution of the target variable

Feature selection

1. Lasso regression
2. Ridge regression
3. Without feature selection

Regression with hyperparameters

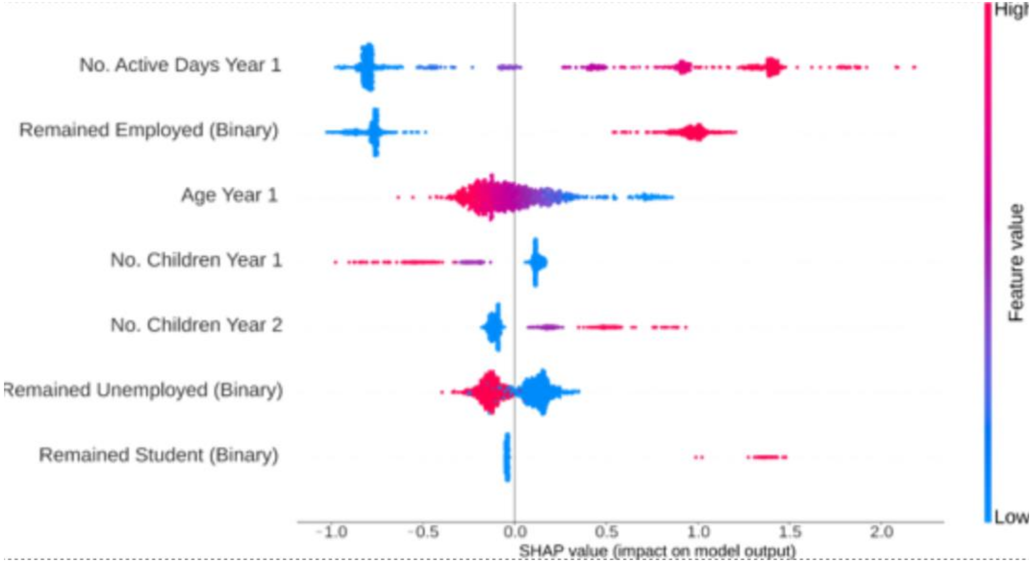
1. Linear regression
2. Lasso regression
3. Ridge regression
4. Neighbors regression (KNN)
5. Support Vector regression (SVR)
6. Random Forests (RFs)
7. Multi-Layer Perceptrons (MLPs)

Stratified four-fold cross-validation on the training set

Purpose	Data split	Linear	Lasso	Ridge	KNN	SVR	RFs	MLPs
Mandatory	Training	0.743	0.756	0.756	0.740	0.740	**0.843**	0.751
	Testing	0.767	0.769	0.769	0.754	0.757	**0.776**	0.775

AI-interpretability: SHapley Additive exPlanations (SHAP)

- **Stability** on active days is confirmed for both mandatory and discretionary acts
- Individuals who remain employed or studying tend to have more active days with mandatory activities
- **Similar conclusions** are obtained in the **traditional** econometric model



Top 7 features

Active days with mandatory activities

Mandatory (zero-state)

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	0.59770	0.44912	1.331	0.183250	
mob.mand	NA	NA	NA	NA	
p.age_gr_1	13.85203	384.00252	0.036	0.971224	
p.age_gr_2	0.79420	0.45933	1.729	0.083804	.
p.age_gr_5	-1.54041	0.25488	-6.044	1.51e-09	***
p.age_gr_6	-1.54949	0.25185	-6.152	7.63e-10	***
hh.childrenUnder10	-0.41149	0.15040	-2.736	0.006221	**
change.hh.childBirthSimpleChildBirth_femChild birth	-2.03146	0.93128	-2.181	0.029158	*
change.hh.childBirthSimpleChildBirth_femSame	-0.35187	0.18297	-1.923	0.054463	.
p.occupationStatus.OHalftime	0.30912	0.36109	0.856	0.391954	
p.occupationStatus.OStudent	-1.15829	0.55680	-2.080	0.037503	*
p.occupationStatus.OUnemployed	-3.24991	0.33871	-9.595	< 2e-16	***
change.p.employmentSimpleSimpleBecome employed	3.85304	0.30434	12.660	< 2e-16	***
change.p.employmentSimpleSimpleBecome unemployed or student	-2.05208	0.44278	-4.635	3.58e-06	***
change.p.employmentSimpleSimpleOther transition	1.47496	0.63804	2.312	0.020794	*
p.mobilityRestrictionUnrestricted	0.89662	0.31639	2.834	0.004599	**
change.p.mobilitySimpleImproved	1.42818	0.44957	3.177	0.001489	**
change.p.mobilitySimpleWorsen	0.23149	0.38590	0.600	0.548603	
change.p.bikSimpleDecreased	-0.30341	0.34238	-0.886	0.375530	
change.p.bikSimpleIncreased	0.74867	0.37045	2.021	0.043283	*
change.hh.sizeSimpleSimpleDecreased	0.09955	0.46111	0.216	0.829067	
change.hh.sizeSimpleSimpleIncreased	-2.43862	0.90248	-2.702	0.006890	**
change.hh.autosSimpleDecreased	-0.70724	0.62567	-1.130	0.258322	
change.hh.autosSimpleIncreased	-0.14199	0.46630	-0.305	0.760744	
days.vacation	-0.50223	0.13097	-3.835	0.000126	***
change.days.vacation	-0.66807	0.13119	-5.092	3.54e-07	***
days.sick	-0.09545	0.10597	-0.901	0.367734	
change.days.sick	-0.30898	0.10354	-2.984	0.002845	**
days.abnormal	-0.36784	0.09760	-3.769	0.000164	***
change.days.abnormal	-0.49861	0.10340	-4.822	1.42e-06	***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Mandatory (count-state)

	Estimate	Std. Error	z value	Pr(>|z|)	
mob.mand	0.616509	0.029403	20.9673	< 2.2e-16	***
p.age_gr_1	1.186824	0.141665	8.3777	< 2.2e-16	***
p.age_gr_5	-0.326057	0.132734	-2.4565	0.014031	*
p.age_gr_6	-2.611645	0.281717	-9.2705	< 2.2e-16	***
hh.childrenUnder10	0.145930	0.049987	2.9194	0.003507	**
change.hh.childBirthSimpleChildBirth_femChild birth	-0.226331	0.207033	-1.0932	0.274299	
change.hh.childBirthSimpleChildBirth_femSame	-0.023493	0.067193	-0.3496	0.726620	
p.occupationStatus.OHalftime	-0.934768	0.091076	-10.2636	< 2.2e-16	***
p.occupationStatus.OStudent	-0.781691	0.132286	-5.9091	3.440e-09	***
p.occupationStatus.OUnemployed	-1.160736	0.203034	-5.7169	1.085e-08	***
change.p.employmentSimpleSimpleBecome employed	1.299448	0.188224	6.9037	5.065e-12	***
change.p.employmentSimpleSimpleBecome unemployed or student	-0.601850	0.223359	-2.6945	0.007049	**
change.p.employmentSimpleSimpleOther transition	-0.481745	0.291382	-1.6533	0.098268	.
p.mobilityRestrictionUnrestricted	0.550539	0.200442	2.7466	0.006021	**
change.p.mobilitySimpleImproved	0.667304	0.313752	2.1269	0.033432	*
change.p.mobilitySimpleWorsen	-0.213609	0.268786	-0.7947	0.426776	
change.p.driverLicenseSimpleLicensed	-0.114513	0.211506	-0.5414	0.588220	
change.p.driverLicenseSimpleUnlicensed	0.633322	0.276070	2.2941	0.021787	*
hh.income	-0.067423	0.017785	-3.7911	0.000150	***
change.hh.incomeSimpleDecreased	0.209387	0.098449	2.1269	0.033432	*
change.hh.incomeSimpleIncreased	0.126856	0.082226	1.5428	0.122886	
hh.econStatus.o	0.121273	0.053336	2.2737	0.022981	*
change.hh.econStatusSimpleImproved	0.179887	0.113598	1.5835	0.113300	
change.hh.econStatusSimpleWorsen	-0.299014	0.132503	-2.2567	0.024030	*
days.vacation	-0.771351	0.065249	-11.8217	< 2.2e-16	***
change.days.vacation	-1.107030	0.053105	-20.8461	< 2.2e-16	***
days.sick	-0.638226	0.060805	-10.4962	< 2.2e-16	***
change.days.sick	-1.023108	0.051415	-19.8991	< 2.2e-16	***
days.abnormal	-0.154733	0.049420	-3.1310	0.001742	**
change.days.abnormal	-0.373363	0.040736	-9.1655	< 2.2e-16	***
1|2	-1.651321	0.276901	-5.9636	2.468e-09	***
2|3	-0.345798	0.271527	-1.2735	0.202830	
3|4	0.810028	0.271022	2.9888	0.002801	**
4|5	2.082102	0.272601	7.6379	2.208e-14	***
5|6	5.958379	0.284226	20.9635	< 2.2e-16	***
6|7	7.987137	0.321837	24.8173	< 2.2e-16	***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Discretionary (zero-state)

```
                                                  Estimate Std. Error z value Pr(>|z|)    
(Intercept)                                        2.19740    0.21348  10.293  < 2e-16 ***
mob.disc                                           0.50472    0.05940   8.496  < 2e-16 ***
p.age_gr_1                                        -1.37448    0.48721  -2.821  0.00479 ** 
change.hh.childBirthSimpleChildBirth_femChild birth -0.21161  0.51658  -0.410  0.68207    
change.hh.childBirthSimpleChildBirth_femSame       0.46323    0.18848   2.458  0.01398 *  
p.occupationStatus.OHalftime                       0.78341    0.36184   2.165  0.03038 *  
p.occupationStatus.OStudent                        1.42588    0.48391   2.947  0.00321 ** 
p.occupationStatus.OUnemployed                     1.61386    0.34245   4.713 2.44e-06 ***
change.p.employmentSimpleSimpleBecome employed    -1.51570    0.48676  -3.114  0.00185 ** 
change.p.employmentSimpleSimpleBecome unemployed or student  2.41495  1.06031  2.278  0.02275 *  
change.p.employmentSimpleSimpleOther transition    0.50759    1.02294   0.496  0.61975    
change.hh.sizeSimpleSimpleDecreased                0.22282    0.48247   0.462  0.64420    
change.hh.sizeSimpleSimpleIncreased                2.44375    0.86389   2.829  0.00467 ** 
change.hh.econStatusSimpleImproved                 0.63243    0.34796   1.818  0.06914 .  
change.hh.econStatusSimpleWorsen                  -0.47294    0.27039  -1.749  0.08027 .  
days.vacation                                      0.51599    0.27389   1.884  0.05958 .  
change.days.vacation                               0.52125    0.23206   2.246  0.02469 *  
days.sick                                         -0.20395    0.07025  -2.903  0.00369 ** 
days.abnormal                                     -0.55640    0.09048  -6.149 7.79e-10 ***
change.days.abnormal                              -0.81648    0.05735 -14.237  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Discretionary (count-state)

```
                                                             Estimate Std. Error  z value  Pr(>|z|)    
mob.disc                                                     0.562579   0.016015  35.1277 < 2.2e-16 ***
p.age_gr_1                                                  -1.239398   0.139390  -8.8916 < 2.2e-16 ***
p.age_gr_2                                                  -0.476883   0.104163  -4.5783 4.689e-06 ***
p.age_gr_5                                                   0.304439   0.078310   3.8876 0.0001012 ***
p.age_gr_6                                                   0.290058   0.083158   3.4880 0.0004866 ***
hh.childrenUnder10                                           0.063615   0.044022   1.4451 0.1484375    
change.hh.childBirthSimpleChildBirth_femChild birth          0.568959   0.155578   3.6571 0.0002551 ***
change.hh.childBirthSimpleChildBirth_femSame                 0.028024   0.043881   0.6386 0.5230617    
p.occupationStatus.OHalftime                                 0.563744   0.075327   7.4840 7.210e-14 ***
p.occupationStatus.OStudent                                  1.148806   0.126770   9.0621 < 2.2e-16 ***
p.occupationStatus.OUnemployed                               1.809254   0.089344  20.2504 < 2.2e-16 ***
change.p.employmentSimpleSimpleBecome employed              -1.082298   0.127885  -8.4631 < 2.2e-16 ***
change.p.employmentSimpleSimpleBecome unemployed or student  1.758478   0.138428  12.7032 < 2.2e-16 ***
change.p.employmentSimpleSimpleOther transition              0.364899   0.221254   1.6492 0.0991005 .  
change.p.bikSimpleDecreased                                 -0.160608   0.077351  -2.0764 0.0378613 *  
change.p.bikSimpleIncreased                                 -0.060044   0.112322  -0.5346 0.5929457    
hh.size.o                                                    0.051776   0.023337   2.2187 0.0265093 *  
hh.econStatus_1                                             -0.131495   0.051859  -2.5356 0.0112250 *  
days.vacation                                                0.165657   0.034332   4.8251 1.399e-06 ***
change.days.vacation                                         0.207182   0.023859   8.6836 < 2.2e-16 ***
days.sick                                                    0.080156   0.031322   2.5591 0.0104938 *  
change.days.sick                                             0.161386   0.022622   7.1340 9.752e-13 ***
days.abnormal                                               -0.742239   0.028298 -26.2297 < 2.2e-16 ***
change.days.abnormal                                        -1.004978   0.025000 -40.1994 < 2.2e-16 ***
1|2                                                         -0.810104   0.095026  -8.5251 < 2.2e-16 ***
2|3                                                          0.620314   0.090297   6.8697 6.432e-12 ***
3|4                                                          1.910365   0.092643  20.6207 < 2.2e-16 ***
4|5                                                          3.001946   0.096788  31.0158 < 2.2e-16 ***
5|6                                                          4.149662   0.101984  40.6895 < 2.2e-16 ***
6|7                                                          5.702366   0.109351  52.1472 < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Selected features (best model)

Mandatory active days:

Base year:
- Household children
- Autos
- Age
- Sick days
- Vacation days
- Mandatory active days

Second year:
- Household children
- Autos
- Sick days
- Vacation days

Transitions:
- Employment (remained same)
- Become employed
- Become unemployed
- Become student
- Change socioeconomic status

Discretionary active days:
- All features in the dataset

Source: Moreno et al. (2024)

Initial status (wave 1)	Change (wave 5, 6)	Sample size	All activities Mean	All activities CV	Mandatory Mean	Mandatory CV	Discretionary Mean	Discretionary CV
		Employment status						
Full-time worker	No	181	5.860	0.178	2.708	0.759	5.082	0.260
Full-time worker	Yes	62	5.828	0.193	2.062	0.926	5.181	0.263
Student	No	28	5.682	0.232	3.037	0.640	5.028	0.296
Student	Yes	13	6.283	0.133	2.501	0.869	5.759	0.190
Pensioner	No	53	5.852	0.194	0.285	3.285	5.794	0.199
Pensioner	Yes	1	6.600	0.094	0.644	1.448	6.511	0.107
Other	No	4	6.604	0.058	0.144	4.174	6.599	0.058
Other	Yes	8	5.768	0.165	0.360	1.512	5.695	0.165
		Mobility restriction						
Strongly restricted	-	4	5.021	0.234	0.102	3.886	4.999	0.231
Somehow restricted	-	26	5.544	0.222	1.679	1.722	5.252	0.254
Not restricted	-	317	5.915	0.177	2.126	0.980	5.309	0.241
		Household size						
1 person	No	97	5.907	0.181	2.271	0.806	5.296	0.252
1 person	Yes	5	6.504	0.106	3.664	0.388	5.850	0.179
2 person	No	147	5.875	0.176	1.766	1.274	5.333	0.229
2 person	Yes	4	6.395	0.128	4.047	0.389	5.233	0.228
3 or more	No	93	5.808	0.192	2.214	1.025	5.224	0.254
3 or more	Yes	4	4.678	0.438	2.017	1.332	4.184	0.444
		Household children						
No children	No	262	5.886	0.178	2.042	1.057	5.305	0.241
No children	Yes	3	6.395	0.128	4.047	0.389	5.233	0.228
With children	No	85	5.799	0.200	2.075	1.082	5.259	0.249
		Household income (Euro/month)						
Under 2000	No	43	5.819	0.218	1.856	1.014	5.458	0.257
Under 2000	Yes	7	6.738	0.044	4.273	0.375	6.126	0.144
2000-4000	No	129	5.881	0.177	2.009	1.249	5.270	0.245
2000-4000	Yes	12	6.060	0.165	2.316	0.856	5.625	0.200
4000-6000	No	84	5.866	0.178	2.084	1.092	5.254	0.241
4000-6000	Yes	7	5.680	0.194	2.505	0.912	4.880	0.254
More than 6000	No	62	5.777	0.193	2.021	0.754	5.214	0.248
		Household autos						
One or more autos	No	154	5.812	0.190	1.763	1.322	5.312	0.237
One or more autos	Yes	94	5.858	0.187	2.210	1.036	5.208	0.258
Zero autos	No	96	5.984	0.165	2.437	0.640	5.346	0.239
Zero autos	Yes	6	5.850	0.176	2.218	0.794	5.415	0.225

Conclusions from passive tracking

- The results of this paper provide a better understanding of **how stable** the **behavior** of individuals is across **long periods of time**
- The main factor was **occupation status**:
  - Full-time employees were the most stable individuals for mandatory, discretionary and all activities
  - Students presented the least stable patterns, with high seasonal variations of their mandatory activities due to the academic year, but they maintained activity levels for recreation or shopping
  - Interestingly, retirees presented relatively stable patterns and relatively high active days
- **Life events** impact **stability**:
  - Employees who became unemployed increased their variability
  - Students who became employed reduced their variability

Source: Moreno et al. (2024)

Conclusions from passive tracking

- Unlike most existing studies on mobile phone data, our dataset included socio-economic data and trip purpose information, allowing us to conduct unprecedented analysis on the stability of travel behavior. Future research will include:
  - Time spent out-of-home
  - Trips by mode
  - Recurrence to visit certain areas/points of interest
- Use of time series analyses
- Analysis of shorter periods without considering the impact of life events to distinguish further activity purposes

Source: Moreno et al. (2024)

Vision of model evolution