Levers for Change?

The Welfare Effects of Germany's Deutschlandticket

Maximilian Amberg[*‡★] Nicolas Koch[*§]

[*]Mercator Research Institute on Global Commons and Climate Change (MCC)
[‡]University of Potsdam [§]IZA – Institute of Labor Economics

BERD@NFDI Workshop
Data Challenge: Mobile Phone Data
LMU, Munich
November 12, 2024

MCC
Mercator Research Institute on
Global Commons and Climate Change

[★]Presenting author: amberg@mcc-berlin.net

Germany's Unprecedented Public Transport Policy Experiment in the Media

Rail Revolution?

Germany's Flat-Rate Train Ticket

The history of the Deutschland Ticket shows how complicated progress is in a country where pettiness is often the order of the day. And how, sometimes, politicians in Germany can find solutions that they weren't even looking for.

Germany gives green light to €49-a-month public transport ticket

Plan for ticket covering regional rail, metro, trams and buses across country follows success of €9 scheme last year

The New York Times

Germany's €9 Monthly Train Pass Has Proved Popular (and a Pleasant Surprise)

To help offset inflation, Germany's government has introduced cheap train passes this summer. While many found chaos and overcrowding on an overburdened system, it has been a relatively smooth ride.

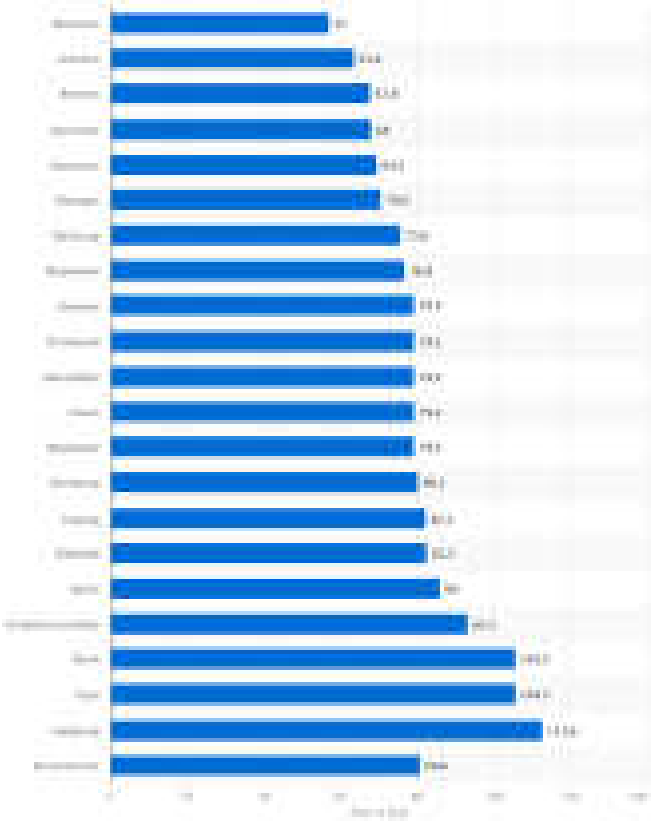
Germany Sets the New Standard for Cheap, National Mass Transit

- €49 buys a month of rides on all urban buses, trams and trains

A Fare Innovation at Large Scale

1. Price reduction (90% and 40%)

Prices for monthly public transit tickets in selected cities (as of July 2021; in Euros)

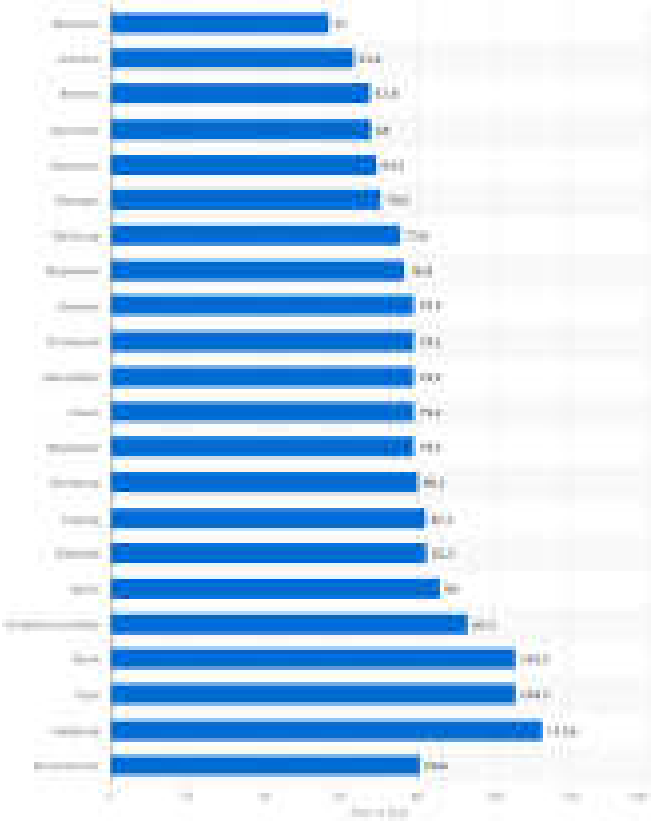


Source: Statista (2021).

A Fare Innovation at Large Scale

1. Price reduction (90% and 40%)

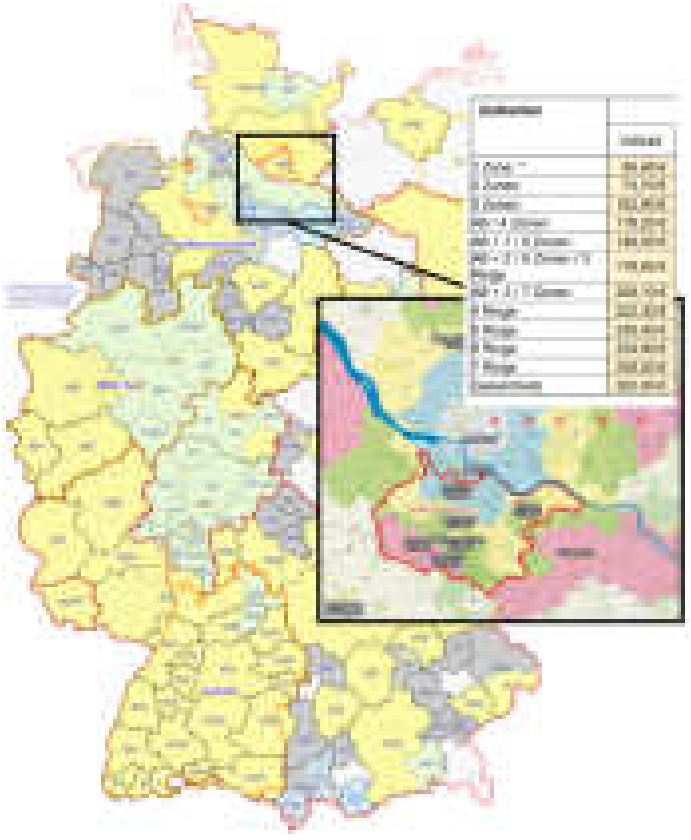
Prices for monthly public transit tickets in selected cities (as of July 2021; in Euros)



Source: Statista (2021).

2. Reduced complexity

Germany's 'tariff-jungle':
Many different transport associations



Source: Based on Dörrbecker (2024).

What This Paper Does

Provides a systematic, comparative ex-post evaluation of the **€49- and €9-ticket** in Germany ...

- ... from a social welfare perspective ...
  1. **Effect of subsidy:** More public transport (PT)? How price sensitive?
  2. **Impact on total mobility:** Modal shift with fewer cars? Or complementary travel (latent demand)?
  3. **Externalities:** Less global & local pollutants, congestion, etc.?

- ... claiming a **causal interpretation** by pairing ...
  1. population-wide GPS/phone-based tracking data from European countries
  2. with recent advances in the Synthetic Control Method (SCM)

  ... to build a credible control group (called 'synthetic Germany')

Related Literature

Endogeneity and measurement challenges make **empirical assessments hard:**

- Strong **variations in price** of PT are **rare** and **not randomly assigned** (Huber et al., 2022; Wallimann et al., 2023)
  - Most literature on role of infrastructure, e.g., Baum-Snow et al. (2017), Gonzalez-Navarro and Turner (2018), Tsivanidis (2018)
- **Observing ridership on one mode of transport is not sufficient** to capture (theoretically ambiguous) overall effects (Christensen and Osman, 2023)
  - Studies focusing on air pollution or CO_2 effect lack clarity on mechanism, e.g., Gohl and Schrauth (2022) and Eibinger and Fernando (2024)
- **Representative, high-frequency data on total mobility** are rare
  - Existing literature based on survey data (Andor et al., 2023) or self-selected GPS tracking (Loder et al., 2023; Guajardo Ortega and Link, 2023)
  - Notable exemption: Liebensteiner et al. (2024)

⇒ **This paper:** Two large-scale policy experiments and novel mobility data can help overcome some of these challenges

Preview of Results

1. **Persistent increase** in train ridership for the €49-ticket
   - BUT no evidence for sticky habits
     (effect of €9-ticket = 0 after end of subsidy)

2. PT riders are **price sensitive** and both programs were effective in inducing more train ridership
   - Higher implied elasticity for permanent €49-ticket

3. **Substitution** away from car travel
   - Stronger in cities and areas of high perceived PT attractiveness
     → Long term implications for **externalities**!

4. **Total mobility** did not increase
   → Little evidence for *latent demand*

Timeline of the Interventions

- The cost of PT plays a role in many European countries
  - In 2018, 🇪🇪 made PT free in most counties
  - In 2020, 🇱🇺 removed all fares completely
  - In 2021, 🇦🇹 launched the "Klimaticket"
  - In 2022, during the national energy crisis, 🇩🇪 and others followed

History of events

Timeline of the Interventions

- The cost of PT plays a role in many European countries
  - In 2018, 🇪🇪 made PT free in most counties
  - In 2020, 🇱🇺 removed all fares completely
  - In 2021, 🇦🇹 launched the "Klimaticket"
  - In 2022, during the national energy crisis, 🇩🇪 and others followed

History of events

Timeline of the Interventions

- The cost of PT plays a role in many European countries
  - In 2018, 🇪🇪 made PT free in most counties
  - In 2020, 🇱🇺 removed all fares completely
  - In 2021, 🇦🇹 launched the "Klimaticket"
  - In 2022, during the national energy crisis, 🇩🇪 and others followed

History of events

Timeline of the Interventions

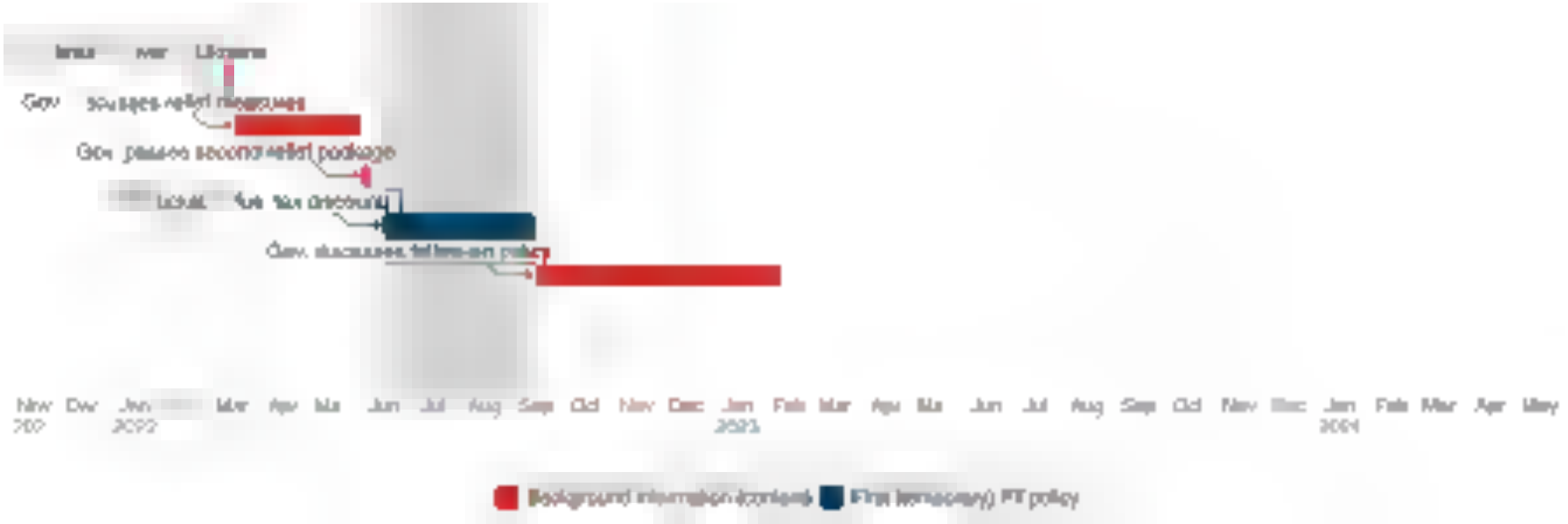
- The cost of PT plays a role in many European countries
  - In 2018, 🇪🇪 made PT free in most counties
  - In 2020, 🇱🇺 removed all fares completely
  - In 2021, 🇦🇹 launched the "Klimaticket"
  - In 2022, during the national energy crisis, 🇩🇪 and others followed

History of events

Timeline of the Interventions

- The cost of PT plays a role in many European countries
  - In 2018, 🇪🇪 made PT free in most counties
  - In 2020, 🇱🇺 removed all fares completely
  - In 2021, 🇦🇹 launched the "Klimaticket"
  - In 2022, during the national energy crisis, 🇩🇪 and others followed

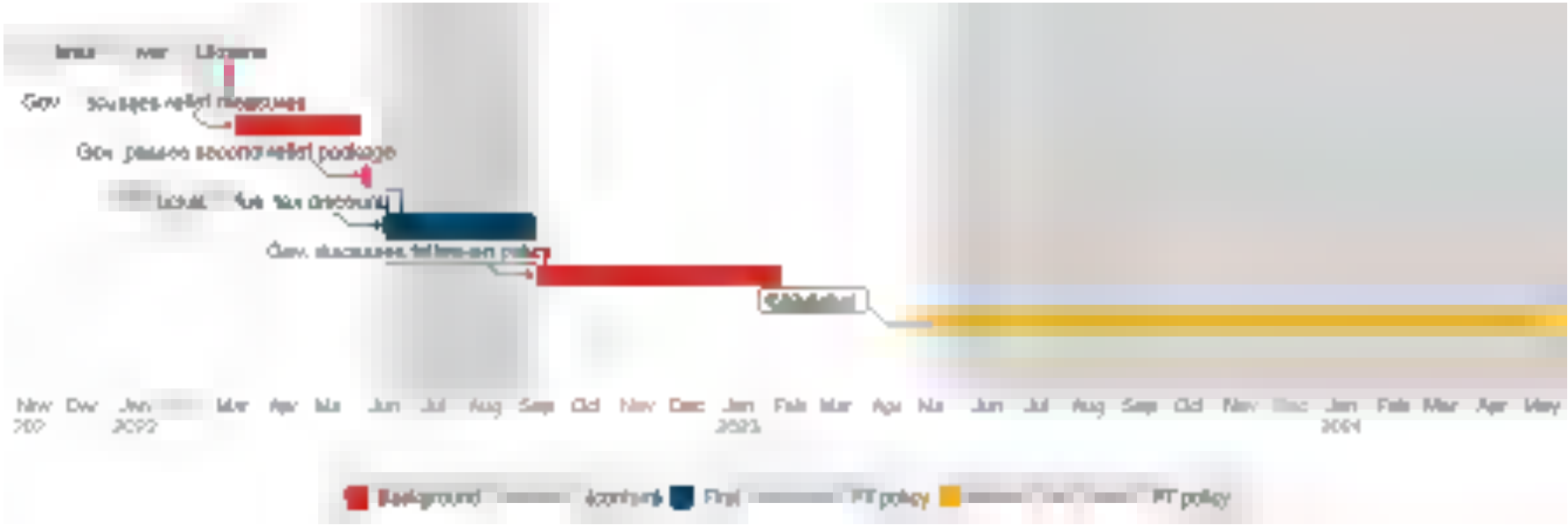
History of events



Timeline of the Interventions

- The cost of PT plays a role in many European countries
  - In 2018, 🇪🇪 made PT free in most counties
  - In 2020, 🇱🇺 removed all fares completely
  - In 2021, 🇦🇹 launched the "Klimaticket"
  - In 2022, during the national energy crisis, 🇩🇪 and others followed

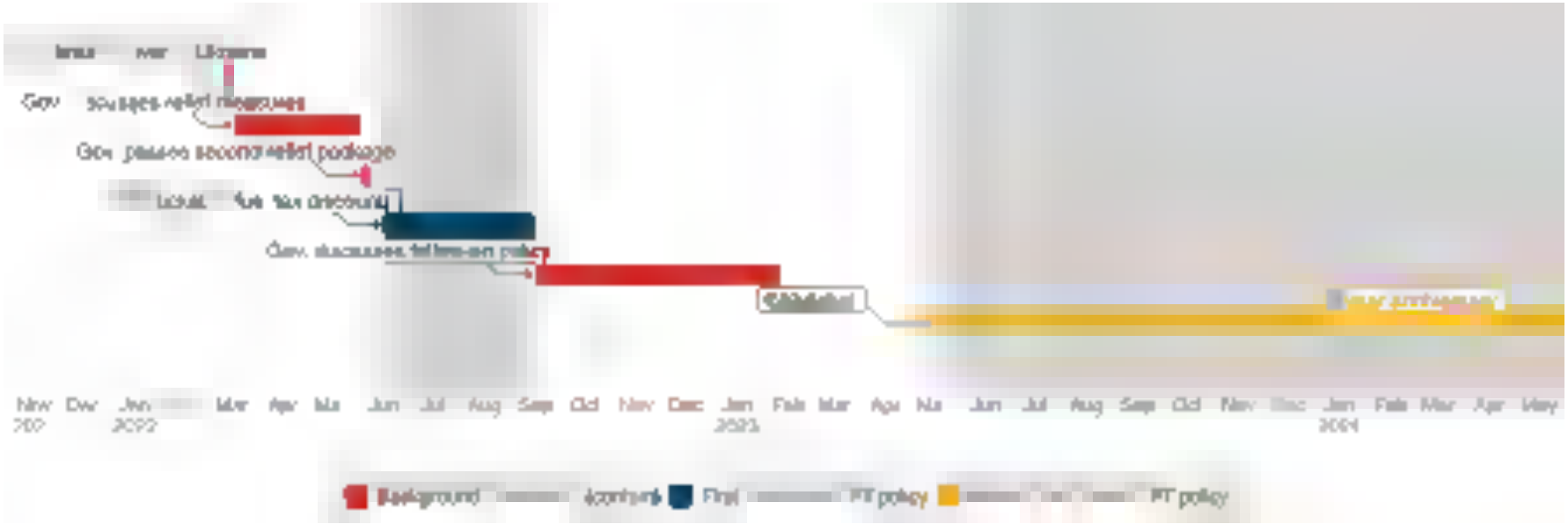
History of events



Timeline of the Interventions

- The cost of PT plays a role in many European countries
  - In 2018, 🇪🇪 made PT free in most counties
  - In 2020, 🇱🇺 removed all fares completely
  - In 2021, 🇦🇹 launched the "Klimaticket"
  - In 2022, during the national energy crisis, 🇩🇪 and others followed

History of events



Comparison of the €9- and €49-ticket

Dimension	€9-ticket	€49-ticket
Program period:	June - August 2022	Since May 2023
Price per month:	**EUR 9** (around EUR 0.3 per day)	**EUR 49** (around EUR 1.6 per day)
Price reduction:	Almost 90% *	Around 40% *
Scope:	Nationwide, all regional PT **	Nationwide, all regional PT **
Overall costs:	EUR 2.5 bn for the 3 months	By 2025, EUR 1.5 bn by gov. and states each

Notes: * We derive the implied price reduction from a comparison to the average price of a monthly ticket in Germany prior to the policy implementations—about €80 according to Statista (2021). ** Long-distance travel by ICE, IC, and EC trains as well as Flixtrains and IC busses was not included.

Data

Instead of **survey data or traditional traffic counts**, we use ...

1. novel,
2. high frequency,
3. nearly real-time generated,

... **mobile phone- and tracking-based data** for Germany and other European countries/regions

Data provided by

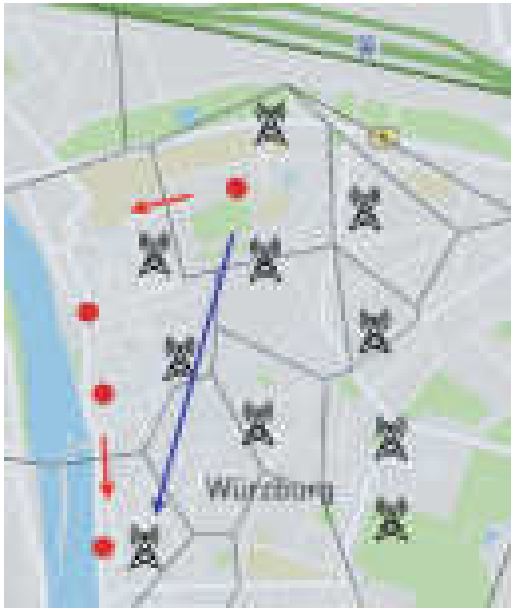
1. TERALYTICS
2. INRIX IQ

Teralytics

TERALYTICS

🇩🇪 (401) + 🇮🇹 (107)

- **Anonymized mobile phone data** of O_2/Telefónica (DEU) and Wind Tre (ITA), processed by Teralytics
  - Market share of O_2/Telefónica in DEU: $\approx \frac{1}{3}$ (≈ 30 million mobile phones)
  - Use demographic data to extrapolate to the total population $\rightarrow \approx 130$ bn of moves in 2023

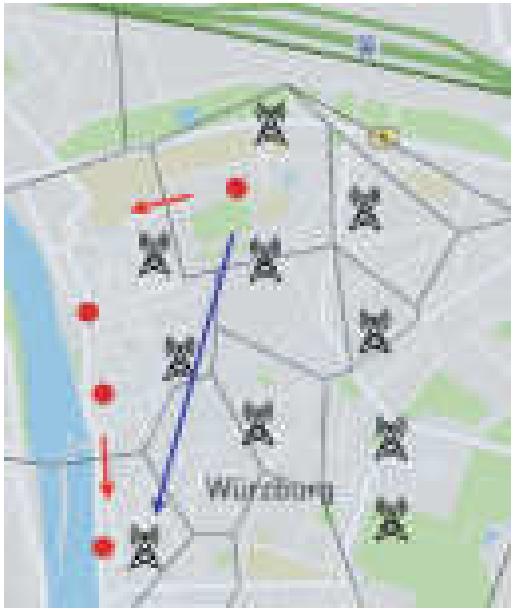


Teralytics

TERALYTICS

🇩🇪 (401) + 🇮🇹 (107)

- **Anonymized mobile phone data** of O_2/Telefónica (DEU) and Wind Tre (ITA), processed by Teralytics
  - Market share of O_2/Telefónica in DEU: $\approx \frac{1}{3}$ (≈ 30 million mobile phones)
  - Use demographic data to extrapolate to the total population $\rightarrow \approx 130$ bn of moves in 2023

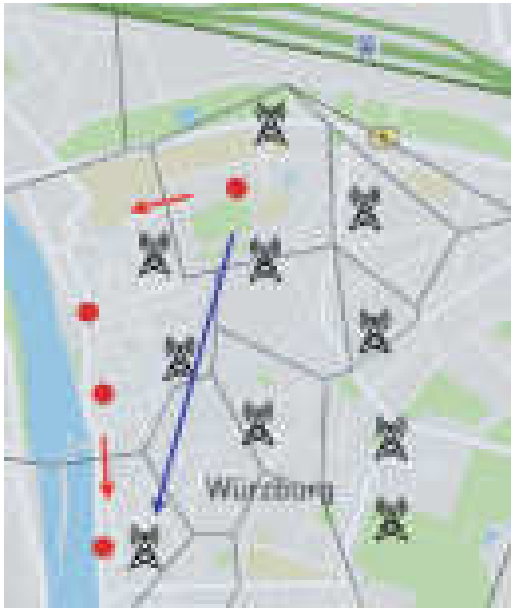


- Since 2020, **daily accurate insights** into the number of movements 🔢
  $\Rightarrow$ Ideal for analysis of total mobility (irrespective of MoT ✈️ 🚗 🚄 🚇 🚋 🚌 🚲 🚶 and distance 📏)

Teralytics

TERALYTICS

🇩🇪 (401) + 🇮🇹 (107)



- **Anonymized mobile phone data** of O_2/Telefónica (DEU) and Wind Tre (ITA), processed by Teralytics
  - Market share of O_2/Telefónica in DEU: $\approx \frac{1}{3}$ (≈ 30 million mobile phones)
  - Use demographic data to extrapolate to the total population $\rightarrow \approx 130$ bn of moves in 2023

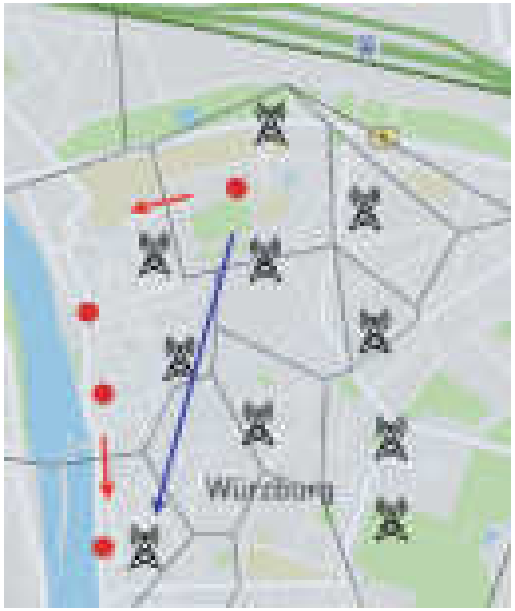
- Since 2020, **daily accurate insights** into the number of movements 🔢
  - $\Rightarrow$ Ideal for analysis of total mobility (irrespective of MoT ✈️🚗🚄🚇🚊🚌🚲🚶 and distance 📏)

- **For trip distances $\geq$ 30 km** differentiation between ...
  - rail mobility 🚄
  - road mobility 🚗
  - air mobility ✈️

Teralytics

TERALYTICS

🇩🇪 (401) + 🇮🇹 (107)



- **Anonymized mobile phone data** of O_2/Telefónica (DEU) and Wind Tre (ITA), processed by Teralytics
  - Market share of O_2/Telefónica in DEU: $\approx \frac{1}{3}$ (≈ 30 million mobile phones)
  - Use demographic data to extrapolate to the total population $\rightarrow \approx 130$ bn of moves in 2023

- Since 2020, **daily accurate insights** into the number of movements 🔢
  - $\Rightarrow$ Ideal for analysis of total mobility (irrespective of MoT ✈️🚗🚄🚇🚊🚌🚲🚶 and distance 📏)

- **For trip distances $\geq$ 30 km** differentiation between ...
  - rail mobility 🚄
  - road mobility 🚗
  - air mobility ✈️

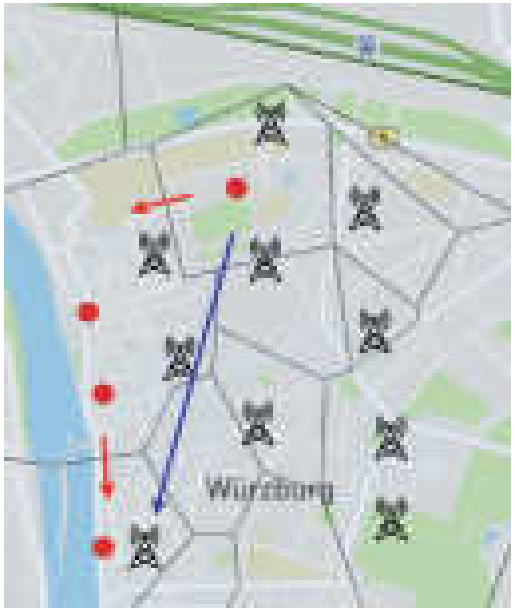
- **For trip distances $<$ 30 km** no differentiation possible

Teralytics

TERALYTICS

🇩🇪 (401) + 🇮🇹 (107)

- **Anonymized mobile phone data** of O_2/Telefónica (DEU) and Wind Tre (ITA), processed by Teralytics
  - Market share of O_2/Telefónica in DEU: $\approx \frac{1}{3}$ (≈ 30 million mobile phones)
  - Use demographic data to extrapolate to the total population $\rightarrow \approx 130$ bn of moves in 2023



- Since 2020, **daily accurate insights** into the number of movements 🔢
  $\Rightarrow$ Ideal for analysis of total mobility (irrespective of MoT ✈️🚗🚄🚇🚊🚌🚲🚶 and distance 📏)

- **For trip distances $\geq$ 30 km** differentiation between ...
  - rail mobility 🚄
  - road mobility 🚗
  - air mobility ✈️

- **For trip distances $<$ 30 km** no differentiation possible

  $\rightarrow$ **Less relevant for env. effects**

INRIX

INRIX IQ

🇩🇪 + 🇪🇺 (7)

- **Anonymized movement data on roads from mobile applications**
  - Coverage of ≈4% of Germany's total car traffic Details
  - Data is representative of the population with car ownership (Koch et al., 2023)

INRIX

INRIX IQ

🇩🇪 + 🇪🇺 (7)

- **Anonymized movement data on roads from mobile applications**
  - Coverage of ≈4% of Germany's total car traffic Details
  - Data is representative of the population with car ownership (Koch et al., 2023)

- Since 2020, **daily accurate insights** into ...
  - number of movements 🔢
  - distance traveled 📏
  - duration of trips ⏳

- App-based data allows for **differentiation** between ...
  - passenger cars 🚗
  - delivery trucks 🚚
  - heavy lorries 🚛

... regardless of distance

INRIX

INRIX IQ

🇩🇪 + 🇪🇺 (7)

- **Anonymized movement data on roads from mobile applications**
  - Coverage of ≈4% of Germany's total car traffic Details
  - Data is representative of the population with car ownership (Koch et al., 2023)

- Since 2020, **daily accurate insights** into ...
  - number of movements 🔢
  - distance traveled 📏
  - duration of trips ⏳

- App-based data allows for **differentiation** between ...
  - passenger cars 🚗
  - delivery trucks 🚚
  - heavy lorries 🚛

... regardless of distance

→ **Essential for env. effects**

Features of High-frequency Mobility Data

TERALYTICS:

→ **Baseline:** Median of same weekday between Jan 3 to Feb 6 of 2020

Features of High-frequency Mobility Data

TERALYTICS:

→ **Highly volatile** time series (workdays, weekends, public holidays, etc.)

Features of High-frequency Mobility Data

TERALYTICS:

→ **Aggregation** with 14-day moving average attenuates magnitude of noise

Features of High-frequency Mobility Data

TERALYTICS:

→ Impact of the **COVID pandemic** clearly visible

Features of High-frequency Mobility Data

TERALYTICS:

→ Impact of the introduction and abolition of the **€9-ticket** is striking

Features of High-frequency Mobility Data

TERALYTICS:

→ Impact of the introduction of the **€49-ticket** is also obvious

Features of High-frequency Mobility Data

TERALYTICS:

→ Impact of **important events** are directly evident

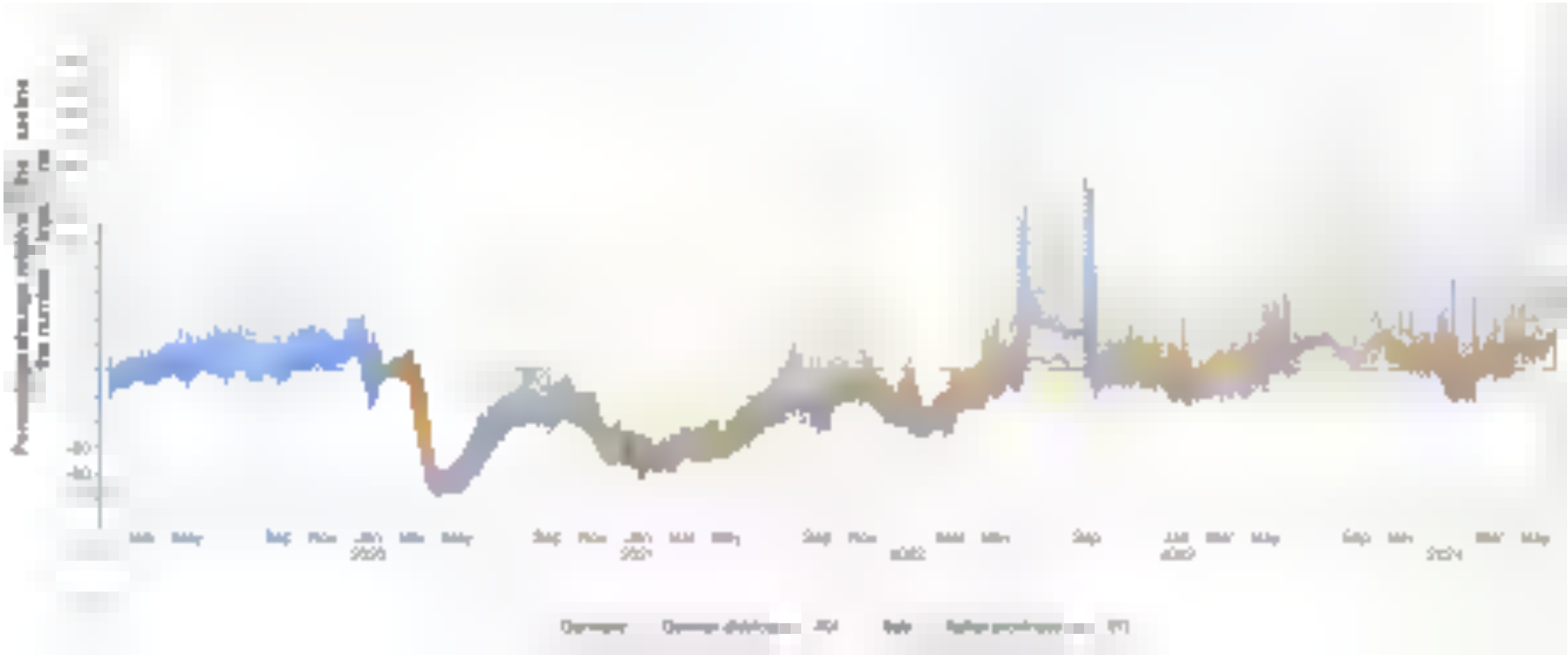
Features of High-frequency Mobility Data

TERALYTICS:

→ **Variation across the 401 districts** is substantial

Features of High-frequency Mobility Data

TERALYTICS:



→ **Overall trend in** 🇮🇹 & its 107 provinces similar to 🇩🇪 **(common support)**

Features of High-frequency Mobility Data

TERALYTICS: &

Consistent with Destatis-data

Consistent with BASt-data

Features of High-frequency Mobility Data

TERALYTICS: & 🚗

→ **Clear indication** for both increase in PT and decrease in car usage

Consistent with Destatis-data Consistent with BASt-data

Features of High-frequency Mobility Data

INRIX IQ :

→ Compared to Teralytics data, **similar patter on the road** for INRIX!

Consistent with BASt-data

Identification Strategy

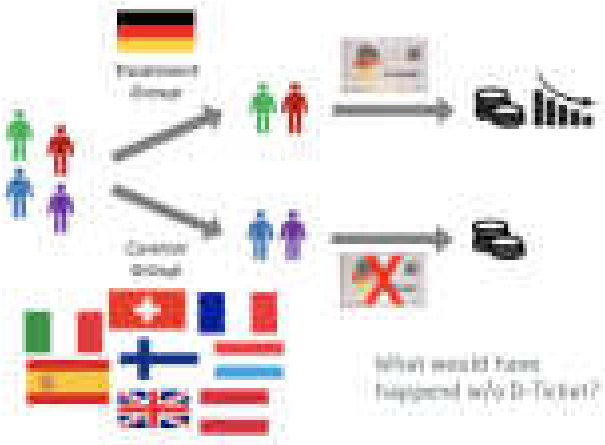
Causal analysis of the D-Ticket's impact

- Instead of simply comparing correlations with a before-and-after analysis, this approach uses a causal research design based on a **control group – similar to clinical trials**
- **However:** difficult to find a good control group

Identification Strategy

Causal analysis of the D-Ticket's impact

- Instead of simply comparing correlations with a before-and-after analysis, this approach uses a causal research design based on a **control group – similar to clinical trials**
- **However:** difficult to find a good control group



💡 **Idea:** Rather than identifying a single country similar to Germany, we construct a **synthetic counterfactual** by combining multiple European countries/regions

Synthetic Control Method (SCM)

(Abadie and Gardeazabal, 2003; Abadie et al., 2010, 2015; Abadie, 2021)

- **SCM** is part of empirical methods awarded with Nobel price in 2021

> "... arguably the most important innovation in the policy evaluation literature in the last 15 years ..." — Athey and Imbens (2017, p.9)

  - **Applications:** minimum wages, tax reforms, German reunion, Brexit, ...

Synthetic Control Method (SCM)

(Abadie and Gardeazabal, 2003; Abadie et al., 2010, 2015; Abadie, 2021)

- **SCM** is part of empirical methods awarded with Nobel price in 2021

> "... arguably the most important innovation in the policy evaluation literature in the last 15 years ..." — Athey and Imbens (2017, p.9)

  - **Applications:** minimum wages, tax reforms, German reunion, Brexit, ...

- **Interest in:** $\alpha_{DEU,t} = Y^1_{DEU,t} - Y^0_{DEU,t}$

Synthetic Control Method (SCM)

(Abadie and Gardeazabal, 2003; Abadie et al., 2010, 2015; Abadie, 2021)

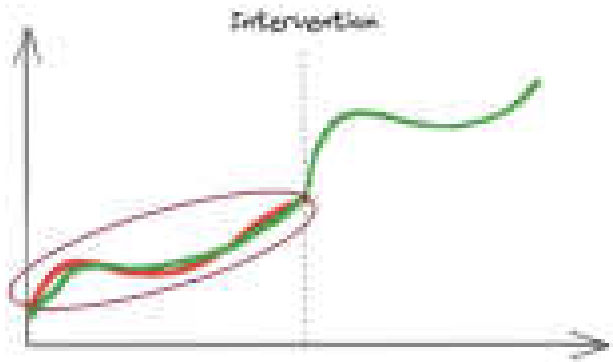
- **SCM** is part of empirical methods awarded with Nobel price in 2021

> "... arguably the most important innovation in the policy evaluation literature in the last 15 years ..." — Athey and Imbens (2017, p.9)

  - **Applications:** minimum wages, tax reforms, German reunion, Brexit, ...

- **Interest in:** $\alpha_{DEU,t} = Y^1_{DEU,t} - Y^0_{DEU,t}$
- **Weight other countries** to match DEU for a long time period pre-treatment:

$$\sum_{j=C_1}^{C_N} w_j^\star Y_{j,1} = Y_{DEU,1},$$
$$\sum_{j=C_1}^{C_N} w_j^\star Y_{j,2} = Y_{DEU,2},$$
$$\dots$$
$$\sum_{j=C_1}^{C_N} w_j^\star Y_{j,T_0} = Y_{DEU,T_0}$$



Synthetic Control Method (SCM)

(Abadie and Gardeazabal, 2003; Abadie et al., 2010, 2015; Abadie, 2021)

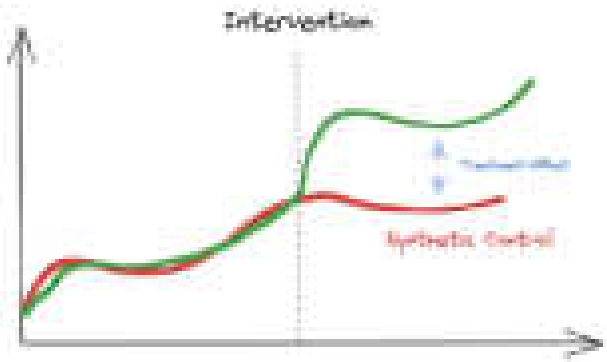
- **SCM** is part of empirical methods awarded with Nobel price in 2021

> "... arguably the most important innovation in the policy evaluation literature in the last 15 years ..." — Athey and Imbens (2017, p.9)

  - **Applications:** minimum wages, tax reforms, German reunion, Brexit, ...

- **Interest in:** $\alpha_{DEU,t} = Y^1_{DEU,t} - Y^0_{DEU,t}$
- **Weight other countries** to match DEU for a long time period pre-treatment:

$$\sum_{j=C_1}^{C_N} w_j^\star Y_{j,1} = Y_{DEU,1},$$
$$\sum_{j=C_1}^{C_N} w_j^\star Y_{j,2} = Y_{DEU,2},$$
$$\dots$$
$$\sum_{j=C_1}^{C_N} w_j^\star Y_{j,T_0} = Y_{DEU,T_0}$$



- **Unbiased estimator** of $\alpha_{DEU,t}$ post-treatment:

$$\alpha_{DEU,t} = Y^1_{DEU,t} - \sum_{j=C_1}^{C_N} w_j^\star Y_{j,t}$$

Synthetic Control Method (SCM)

(Abadie and Gardeazabal, 2003; Abadie et al., 2010, 2015; Abadie, 2021)

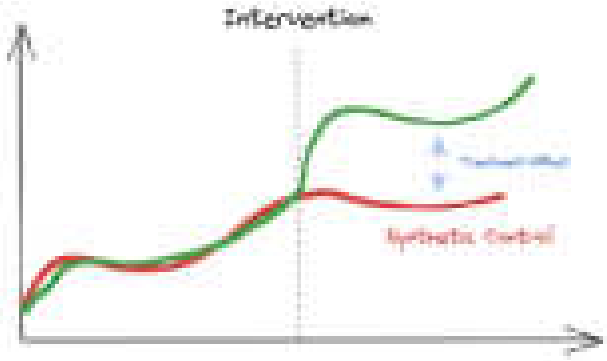
- **SCM** is part of empirical methods awarded with Nobel price in 2021

> "... arguably the most important innovation in the policy evaluation literature in the last 15 years ..." — Athey and Imbens (2017, p.9)

  - **Applications:** minimum wages, tax reforms, German reunion, Brexit, ...

- **Interest in:** $\alpha_{DEU,t} = Y^1_{DEU,t} - Y^0_{DEU,t}$
- **Weight other countries** to match DEU for a long time period pre-treatment:

$$\sum_{j=C_1}^{C_N} w_j^\star Y_{j,1} = Y_{DEU,1},$$
$$\sum_{j=C_1}^{C_N} w_j^\star Y_{j,2} = Y_{DEU,2},$$
$$\dots$$
$$\sum_{j=C_1}^{C_N} w_j^\star Y_{j,T_0} = Y_{DEU,T_0}$$



- **Unbiased estimator** of $\alpha_{DEU,t}$ post-treatment:

$$\alpha_{DEU,t} = Y^1_{DEU,t} - \sum_{j=C_1}^{C_N} w_j^\star Y_{j,t}$$

- **In practice:** $W^* = argmin(Y_{\mathrm{DEU}} - Y_0 W) = argmin(\sqrt{(Y_{DEU} - Y_0 W)' V (Y_{DEU} - Y_0 W)})$

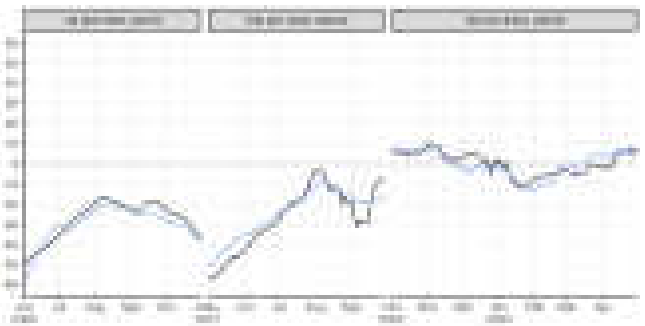
Implementation Details

- SCM weights determined solely on **pre-treatment outcomes**
  - Prevents cherry-picking or specification searching (Ferman et al., 2020)

Implementation Details

- SCM weights determined solely on **pre-treatment outcomes**
  - Prevents cherry-picking or specification searching (Ferman et al., 2020)

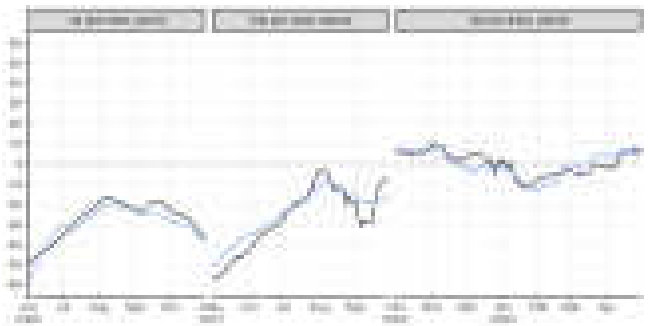
- **Selected pre-treat. period** based on:
  1. Data from 2020 onwards
  2. Exclusion strict lockdowns
  3. Consideration of seasonal trends
  4. Separate analysis of €9-ticket



Implementation Details

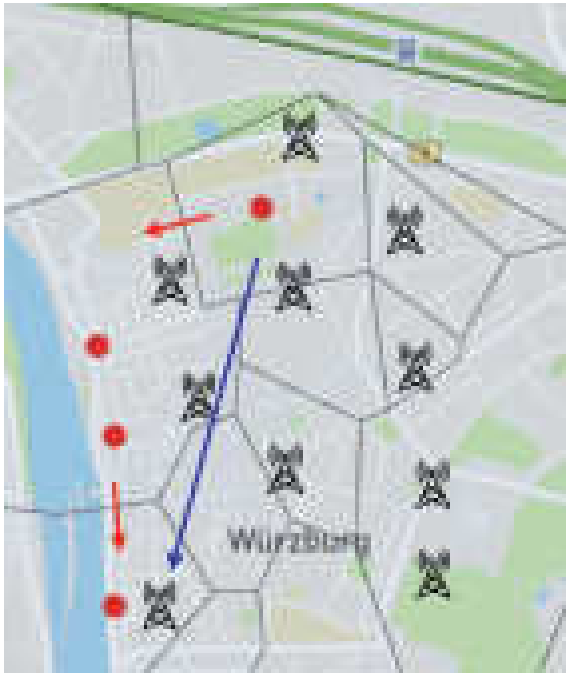
- SCM weights determined solely on **pre-treatment outcomes**
  - Prevents cherry-picking or specification searching (Ferman et al., 2020)

- **Selected pre-treat. period** based on:
  1. Data from 2020 onwards
  2. Exclusion strict lockdowns
  3. Consideration of seasonal trends
  4. Separate analysis of €9-ticket



- Use **flexible extensions** of SCM:
  1. **Augmented SCM** (Ben-Michael et al., 2021) Details
     - Allows negative weights
     - Reduces distortions from poor pre-treatment fit using ML tools
     - Applied in case of country-level data (INRIX)
  2. **Partially Pooled SCM** (Ben-Michael et al., 2022) Details
     - Enables multiple "treated units" (e.g., all districts in Germany rather than only Germany as a whole)
     - Applied in the case of region-level data (Teralytics)

Question 1️⃣:
Do we see an increase in the use of (rail-based) public transport?

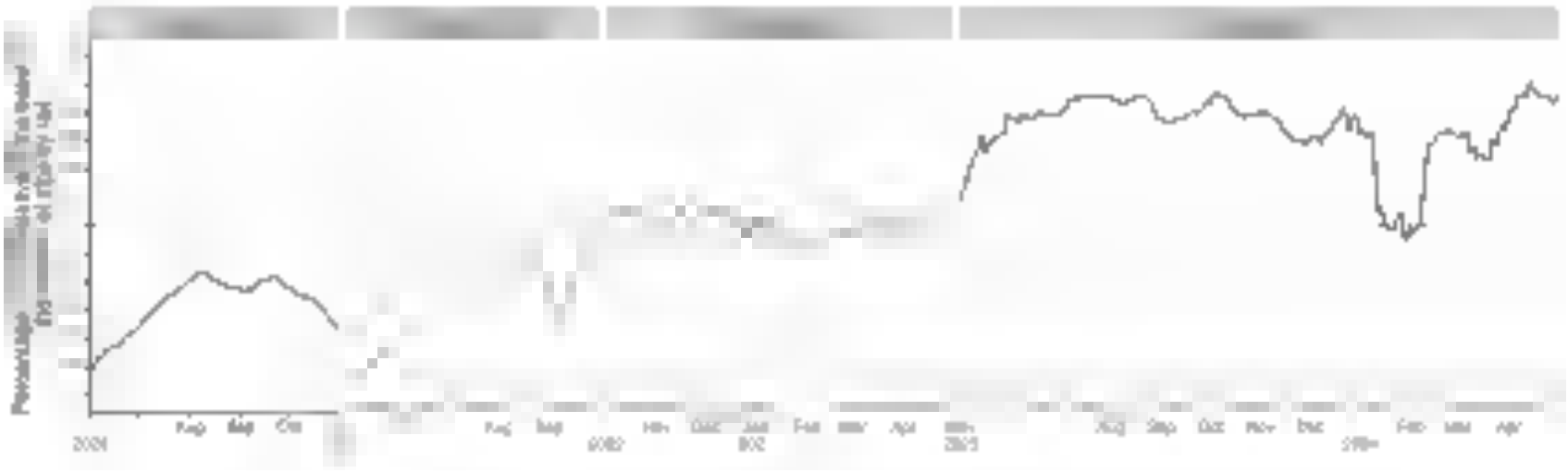


Teralytics/Telefónica

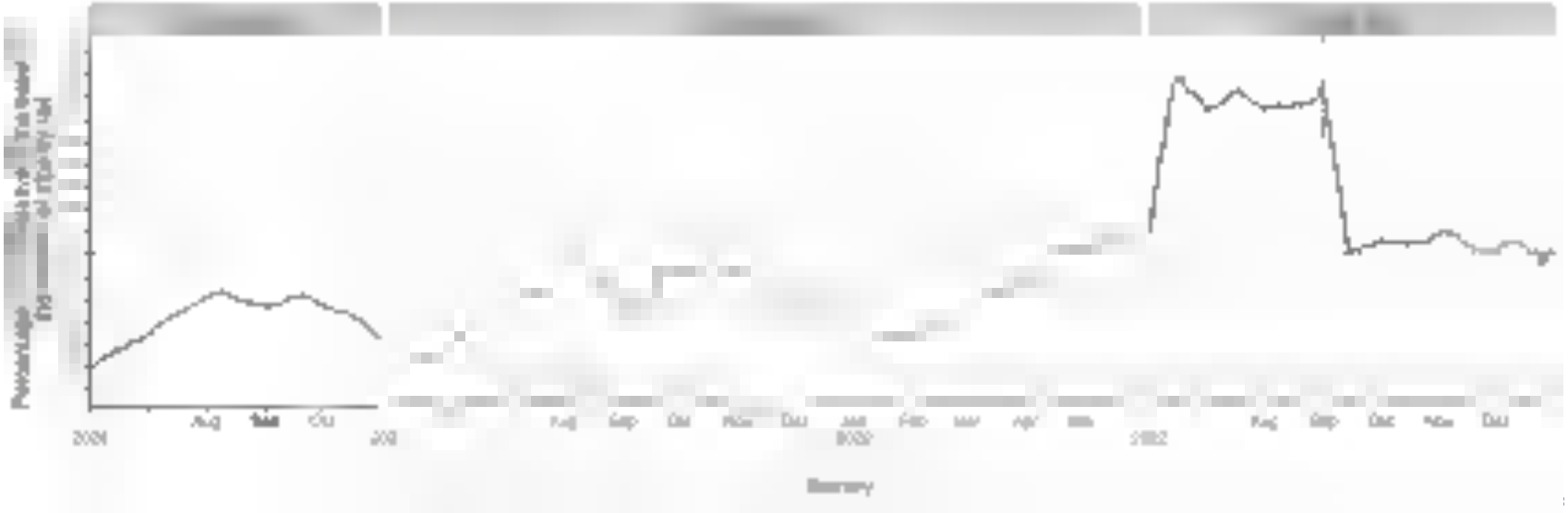
- Based on cell towers
- 🇩🇪 and 🇮🇹
  - ⇒ Subregional level
  - ⇒ Partially pooled SCM

Path of Baseline Rail Mobility (DE vs. Synthetic DE)

€49-ticket



€9-ticket



Path of Baseline Rail Mobility (DE vs. Synthetic DE)

€49-ticket

€9-ticket

Path of Baseline Rail Mobility (DE vs. Synthetic DE)

€49-ticket

€9-ticket

Path of Baseline Rail Mobility (DE vs. Synthetic DE)

€49-ticket

€9-ticket

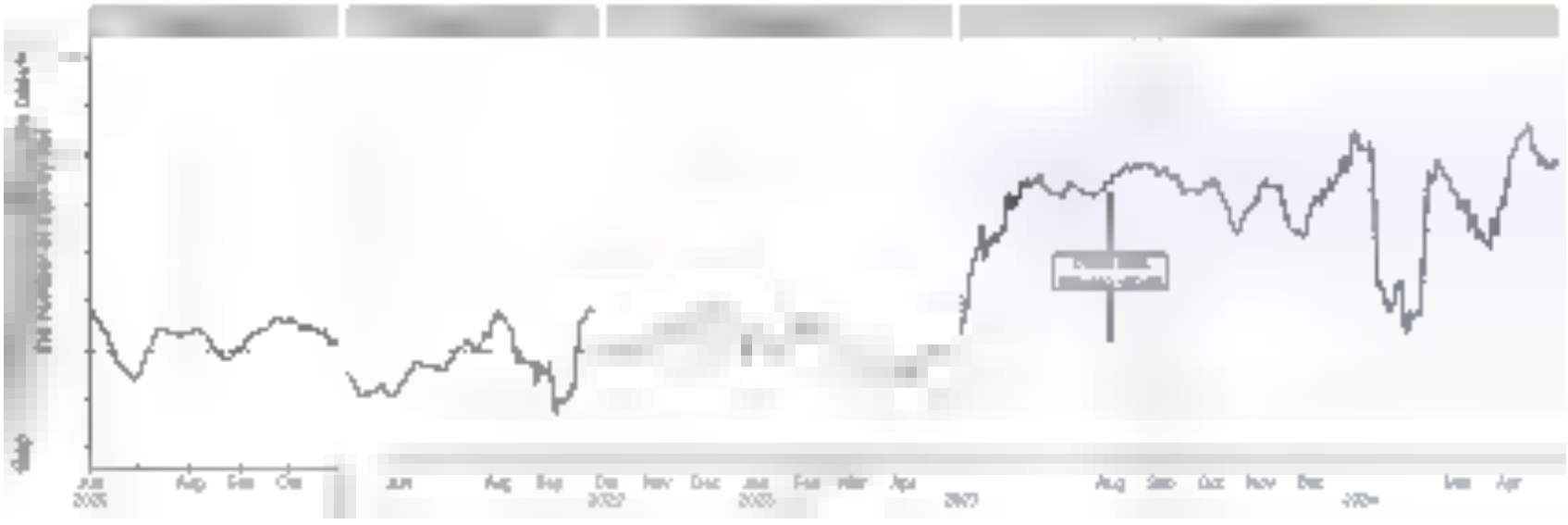
Path of Baseline Rail Mobility (DE vs. Synthetic DE)

€49-ticket

€9-ticket

Gap in Baseline Rail Mobility (btw. DE and Synthetic DE)

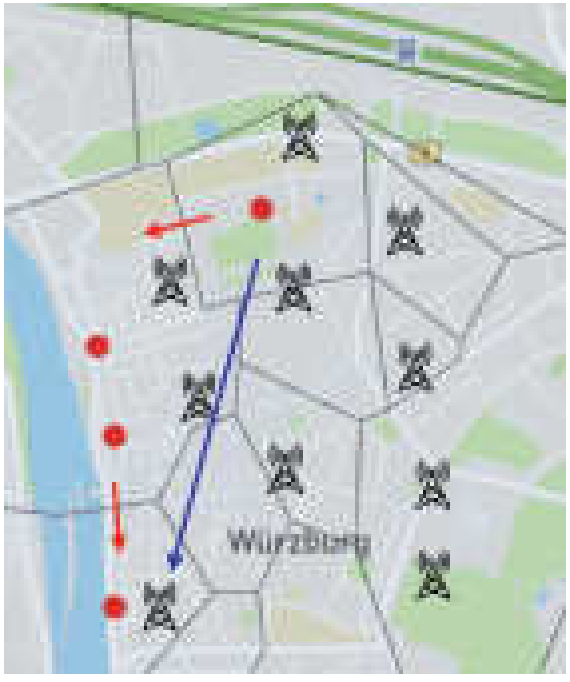
€49-ticket Implied elasticities



€9-ticket

Question 2️⃣:

Do we see a corresponding decrease in the use of cars?



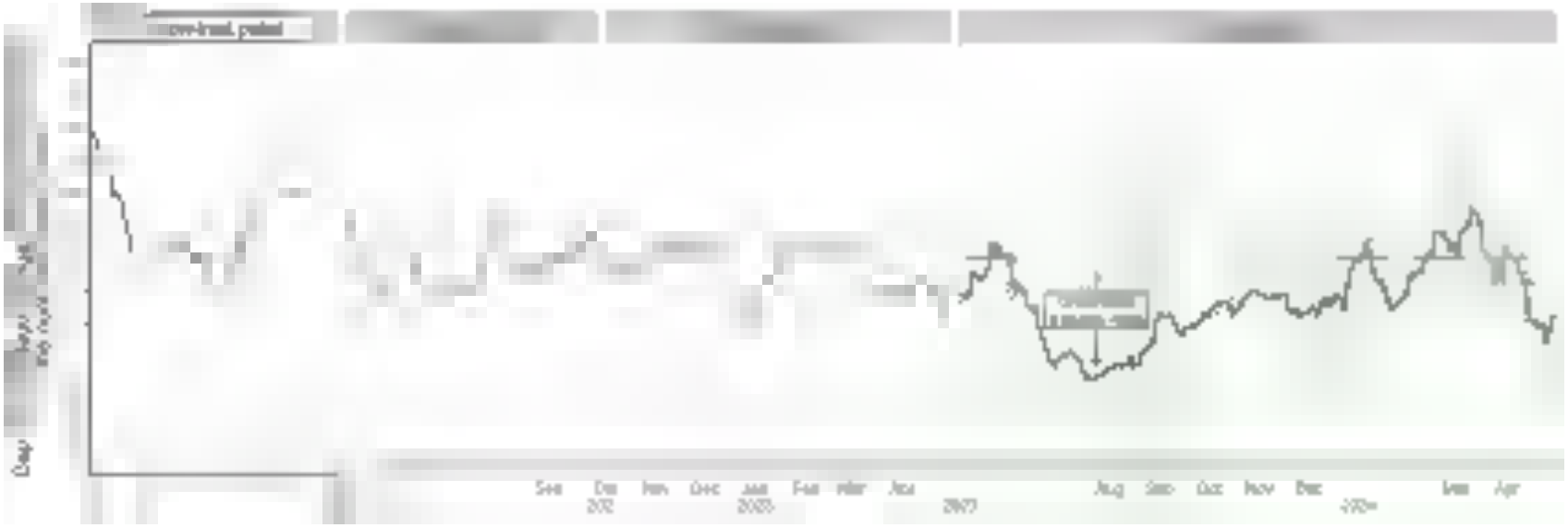
Extensive Margin: number of trips

Telefónica/Teralytics

- Based on cell towers
- 🇩🇪 and 🇮🇹
  - ⇒ Subregional level
  - ⇒ Partially pooled SCM

Gap in Baseline Car Trips (btw. DE and Synthetic DE)

€49-ticket



€9-ticket

Question 2️⃣:

Do we see a corresponding decrease in the use of cars?

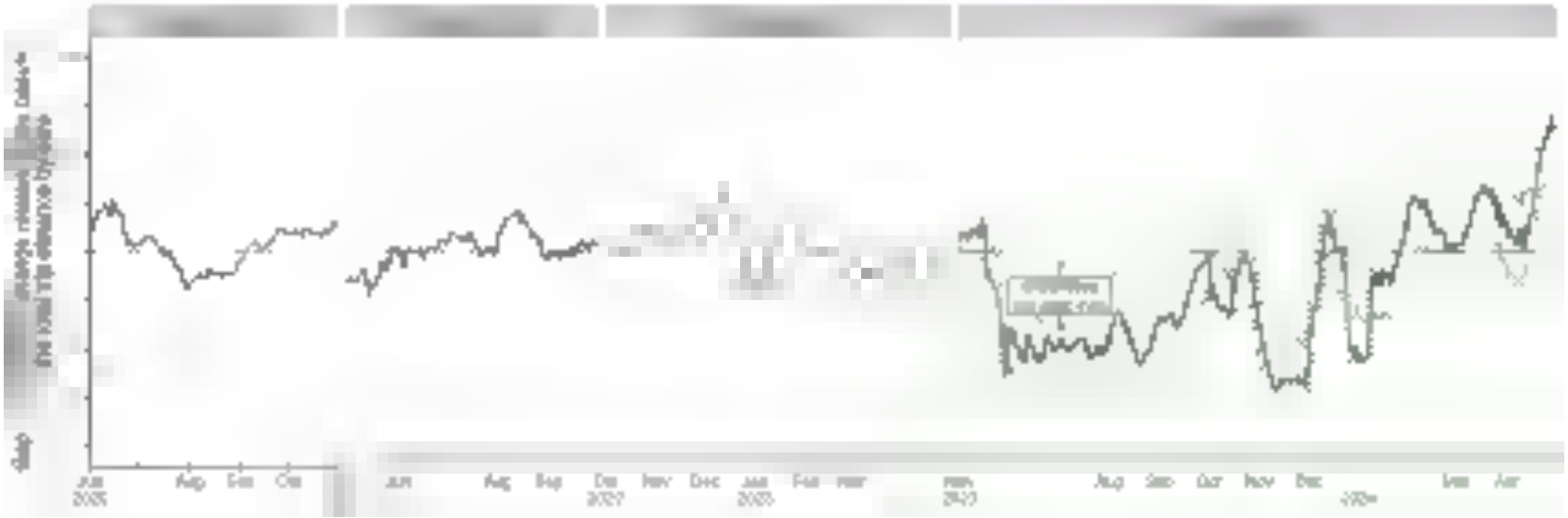
Intensive Margin: km traveled

INRIX

- Based on GPS signals from connected vehicles
- 🇩🇪 and 🇪🇺+
  - ⇒ National level
  - ⇒ Augmented SCM

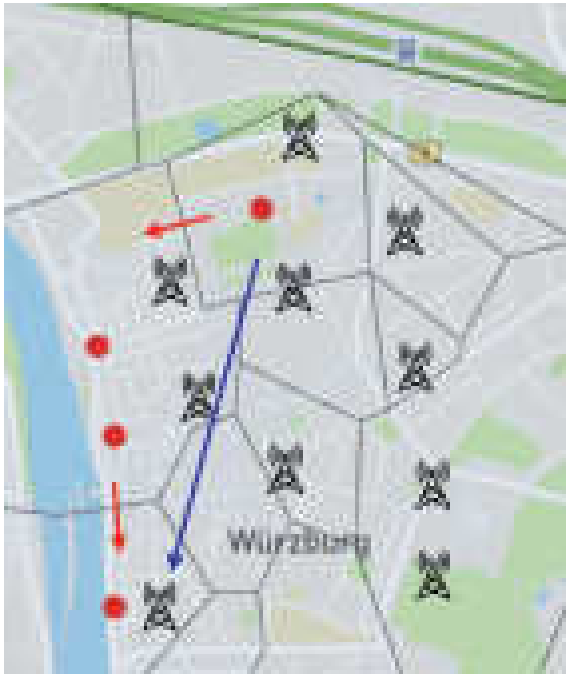
Gap in Baseline Car Trips (btw. DE and Synthetic DE)

€49-ticket Placebo test with trucks: zero effect



€9-ticket

Question 3️⃣:
Do we see an increase in total mobility?



Overall Mobility: all modes of transport

Telefónica/Teralytics

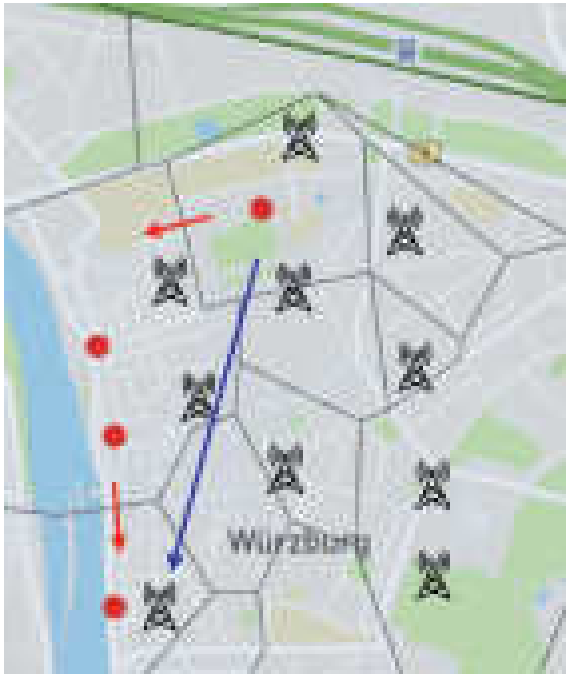
- Based on cell towers
- 🇩🇪 and 🇮🇹
  - ⇒ Subregional level
  - ⇒ Partially pooled SCM

Gap in Baseline Total Mobility (btw. DE and Synthetic DE)

€49-ticket

€9-ticket

Question 4️⃣:
How large is the modal shift?



Modal split: share of trips by rail

Telefónica/Teralytics

- Based on cell towers
- 🇩🇪 and 🇮🇹
  - ⇒ Subregional level
  - ⇒ Partially pooled SCM

Path of Baseline Modal Share of Rail (DE vs. Synthetic DE)

€49-ticket

€9-ticket

Gap in Modal Share of Rail (btw. DE and synthetic DE)

€49-ticket

€9-ticket

Question 5️⃣:
Do effects (modal shift responses) differ <u>across districts</u>?

<u>Modal split</u>: share of trips by rail

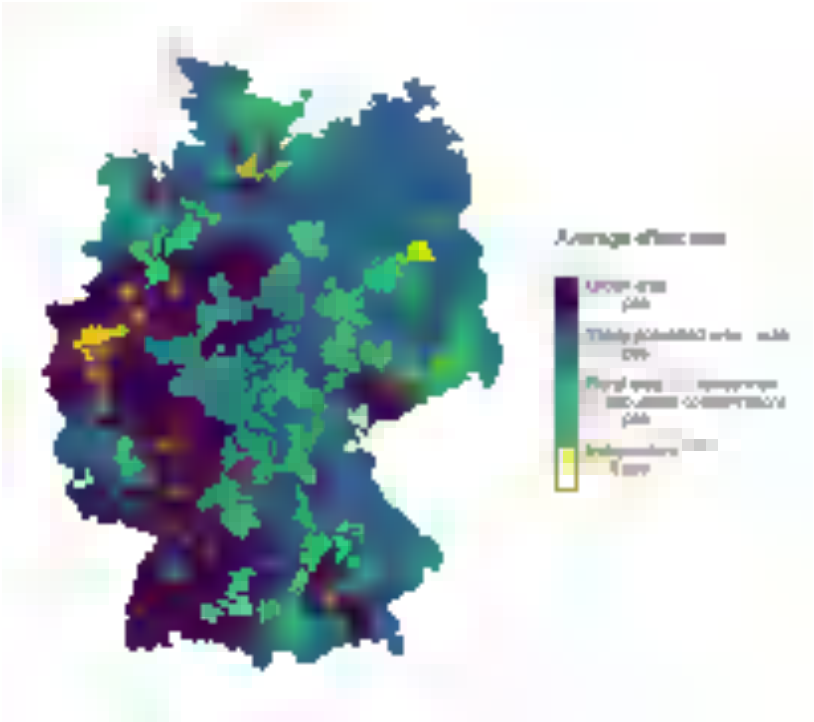
Telefónica/Teralytics

- Based on cell towers
- 🇩🇪 and 🇮🇹
  - ⇒ Subregional level
  - ⇒ Partially pooled SCM

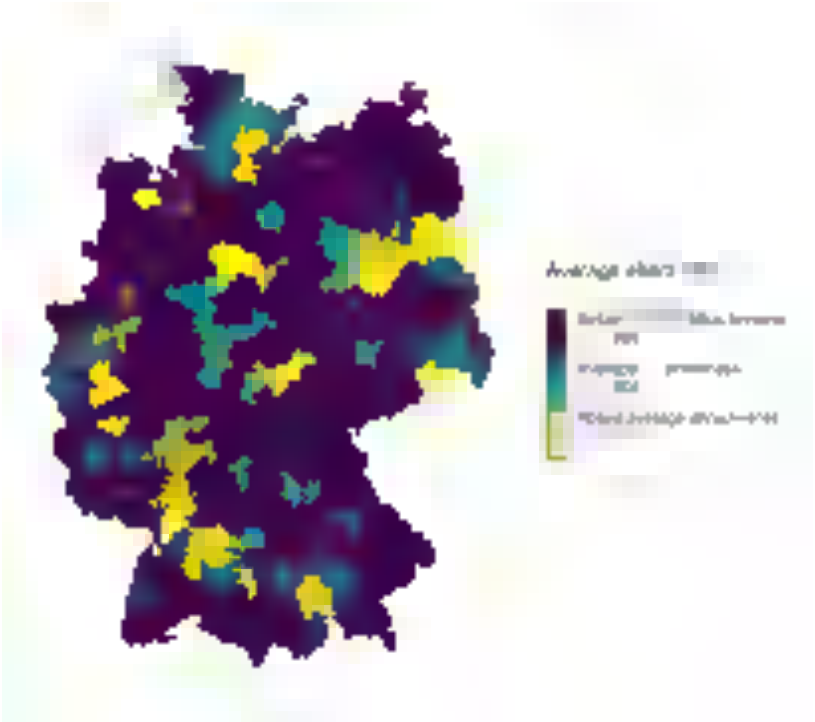
Effect Heterogeneity: Modal Share of Rail

€49-ticket

(a) Settlement pattern
(according to BBSR, 2021)



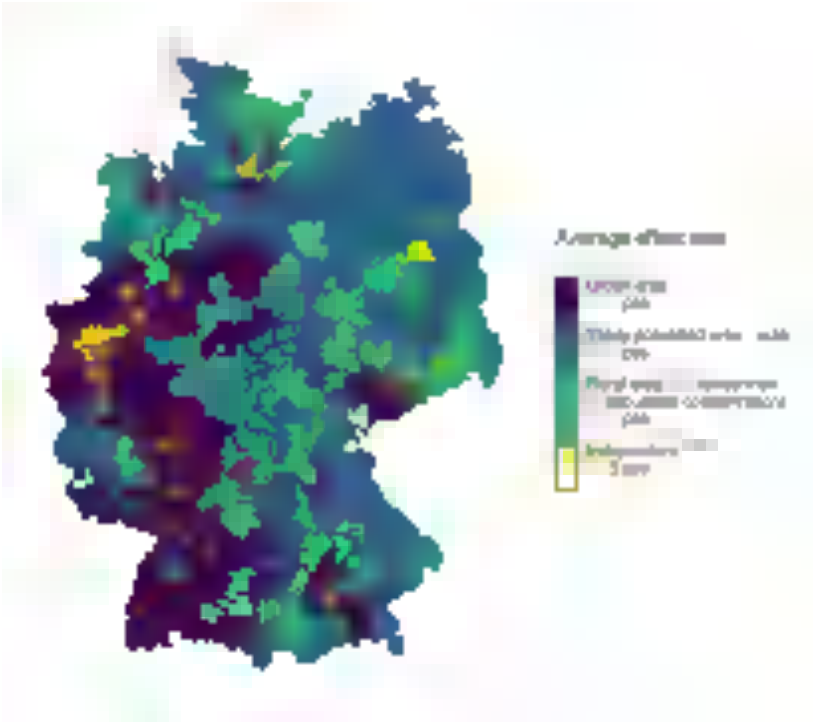
(b) Perceived attractiveness of local PT
(according to BMWK, 2024)



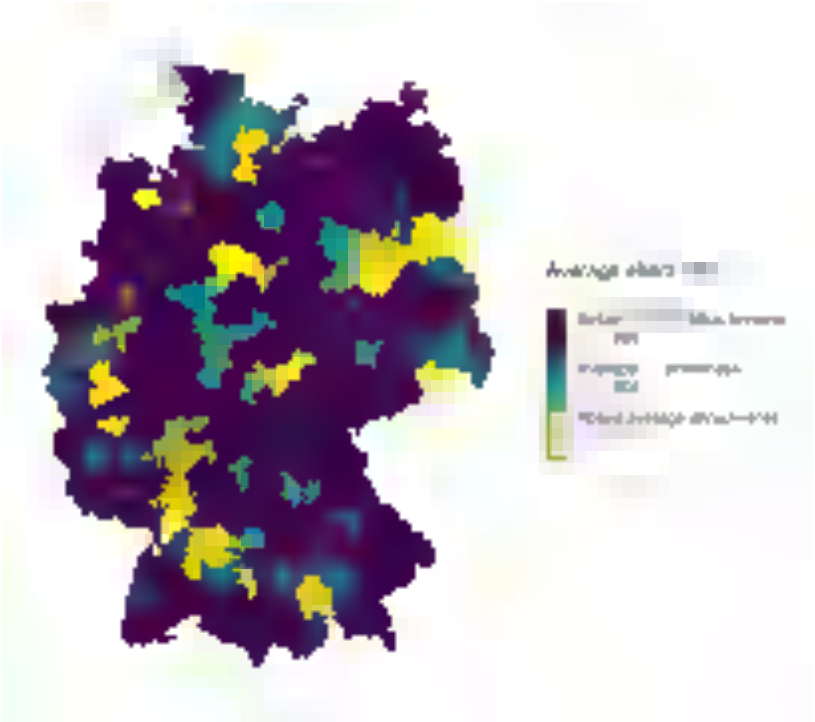
Effect Heterogeneity: Modal Share of Rail

€9-ticket

(a) Settlement pattern
(according to BBSR, 2021)



(b) Perceived attractiveness of local PT
(according to BMWK, 2024)



Takeaways

1. **Persistent increase** in train ridership for the €49-ticket
   - BUT no evidence for sticky habits
     (effect of €9-ticket = 0 after end of subsidy)

2. PT riders are **price sensitive** and both programs were effective in inducing more train ridership
   - Higher implied elasticity for permanent €49-ticket
   - Role of subsidy persistence and salience (similar to tax literature)
     (Li et al., 2014; Andersson, 2019)

3. **Substitution** away from car travel
   - Stronger in cities and areas of high perceived PT attractiveness

   → Necessary condition for long term implications for **externalities**!

4. **Total mobility** did not increase

   → Little evidence for *latent demand*

Ariadne D-Ticket Impact Tracker

Interactive Dashboard: Link

Summary of main results:

„Ariadne kompakt“: Link

Emission reduction

Impact of price increase

Work-in-progress

1 Additional dimensions

1. Commuting (by train or car)
   - Focus on trips to major cities (from 6-9 am)
2. Effect on active mobility
   - Bike counters (EcoCounter)
   - Pedestrian frequencies (hystreet)

2 External effects (negative and positive)

1. Quantification
   - Global pollutants: CO_2 emissions (EU Commission, 2024a)
   - Local pollutants: air quality (EEA, 2024; EU Commission, 2024b)
   - Congestion (TomTom Congestion Index)
   - Tourism indices (Eurostat, 2024)
   - Retail (hystreet)
   - Accidents?
2. Welfare analysis
   - Monetarization
   - Cost-Benefit-Analysis

3 Disentangle price effect from information effect

- Flat rate (rather than complex price scheme) plays a role

Feedback

Thanks for your attention!

Comments? Questions? Suggestions?

Maximilian Amberg
amberg@mcc-berlin.net

MCC
Mercator Research Institute on
Global Commons and Climate Change

KOPERNIKUS PROJEKTE

Bundesministerium für Bildung und Forschung

References I

Abadie, A. (2021). Using Synthetic Controls: Feasibility, Data Requirements, and Methodological Aspects. *Journal of Economic Literature*, 59(2):391–425.

Abadie, A., Diamond, A., and Hainmueller, J. (2010). Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program. *Journal of the American Statistical Association*, 105(490):493–505.

Abadie, A., Diamond, A., and Hainmueller, J. (2015). Comparative Politics and the Synthetic Control Method. *American Journal of Political Science*, 59(2):495–510.

Abadie, A. and Gardeazabal, J. (2003). The Economic Costs of Conflict: A Case Study of the Basque Country. *American Economic Review*, 93(1):113–132.

Abadie, A. and L'Hour, J. (2021). A Penalized Synthetic Control Estimator for Disaggregated Data. *Journal of the American Statistical Association*, 116(536):1817–1834.

Agora Verkehrswende (2024). Vorboten der Mobilitätswende? Analyse des Personenverkehrs in Deutschland vor, während und nach der Coronapandemie (2019–2023). Technical report. Available at: https://www.agora-verkehrswende.de/veroeffentlichungen/vorboten-der-mobilitaetswende/#charts(accessed: November 08, 2024).

Andersson, J. J. (2019). Carbon Taxes and CO_2 Emissions: Sweden as a Case Study. *American Economic Journal: Economic Policy*, 11(4):1–30.

Andor, M. A., Dehos, F. T., Gillingham, K. T., Hansteen, S., and Tomberg, L. (2023). Germany: Luring Drivers Onto Public Transport. *Nature*, 618(7967):907–907.

Athey, S. and Imbens, G. W. (2017). The State of Applied Econometrics: Causality and Policy Evaluation. *The Journal of Economic Perspectives*, 31(2):3–32.

Baum-Snow, N., Brandt, L., Henderson, J. V., Turner, M. A., and Zhang, Q. (2017). Roads, Railroads, and Decentralization of Chinese Cities. *The Review of Economics and Statistics*, 99(3):435–448.

Ben-Michael, E., Feller, A., and Rothstein, J. (2021). The Augmented Synthetic Control Method. *Journal of the American Statistical Association*, 116(536):1789–1803.

Ben-Michael, E., Feller, A., and Rothstein, J. (2022). Synthetic Controls with Staggered Adoption. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 84(2):351–381.

References II

Christensen, P. and Osman, A. (2023). The Demand for Mobility: Evidence from an Experiment with Uber Riders.

Donohue, J. J., Aneja, A., and Weber, K. D. (2019). Right-to-Carry Laws and Violent Crime: A Comprehensive Assessment Using Panel Data and a State-Level Synthetic Control Analysis. *Journal of Empirical Legal Studies*, 16(2):198–247.

Dube, A. and Zipperer, B. (2015). Pooling Multiple Case Studies Using Synthetic Controls: An Application to Minimum Wage Policies. Working paper DP No. 8944, Institute for the Study of Labor (IZA).

Dörrbecker, M. (2024). Map of Transport Associations and Fare Networks in Germany. Available at: https://commons.wikimedia.org/wiki/File:Karte_der_Verkehrsverb%C3%BCnde_und_Tarifverb%C3%BCnde_in_Deutschland.png (accessed: June 19, 2024).

EEA (2024). Air Quality Download Service. Available at: https://eeadmz1-downloads-webapp.azurewebsites.net/ (accessed: February 01, 2024).

Eibinger, T. and Fernando, S. (2024). Does Free Public Transport Reduce Carbon Emissions? Causal Evidence from Luxembourg. Leuven, Belgium.

EU Commission (2024a). EDGAR v8.0 - Emissions Database for Global Atmospheric Research: Global Greenhouse Gas Emissions. Available at: https://edgar.jrc.ec.europa.eu/report_2023 (accessed: November 04, 2024).

EU Commission (2024b). EDGAR v8.1 - Emissions Database for Global Atmospheric Research: Global Air Pollutant Emissions. Available at: https://edgar.jrc.ec.europa.eu/report_2023 (accessed: November 04, 2024).

Eurostat (2024). Short-Stay Accommodation Offered via Collaborative Economy Platforms by Months, Residence of the Guest and NUTS1 and NUTS2 Regions - Experimental Statistics. https://ec.europa.eu/eurostat/databrowser/explore/all/all_themes (accessed: February 01, 2024).

Ferman, B., Pinto, C., and Possebom, V. (2020). Cherry Picking with Synthetic Controls. *Journal of Policy Analysis and Management*, 39(2):510–532.

Gohl, N. and Schrauth, P. (2022). Ticket to Paradise? The Effect of a Public Transport Subsidy on Air Quality. *CEPA Discussion Papers*. Number: 50 Publisher: Center for Economic Policy Analysis.

Gonzalez-Navarro, M. and Turner, M. A. (2018). Subways and Urban Growth: Evidence From Earth. *Journal of Urban Economics*, 108:85–106.

References III

Guajardo Ortega, M. F. and Link, H. (2023). Estimating mode choice inertia and price elasticities after a price intervention: Evidence from three months of almost fare-free public transport in Germany. Working Paper 2052, DIW Discussion Papers.

Huber, M., Meier, J., and Wallimann, H. (2022). Business Analytics Meets Artificial Intelligence: Assessing the Demand Effects of Discounts on Swiss Train Tickets. *Transportation Research Part B: Methodological*, 163:22–39.

KCW (2024). Wandel auf Straßen und Schienen: Verkehrsentwicklung in Deutschland 2019 - 2023. Report on the impact of the COVID-19 pandemic on transportation demand commissioned by Agora Verkehrswende.

Koch, N., Ritter, N., Rohlf, A., and Thies, B. (2023). Machine Learning from Big GPS Data about the Heterogeneous Costs of Congestion.

Li, S., Linn, J., and Muehlegger, E. (2014). Gasoline Taxes and Consumer Behavior. *American Economic Journal: Economic Policy*, 6(4):302–342.

Liebensteiner, M., Losert, J., Necker, S., Neumeier, F., Paetzold, J., and Wichert, S. (2024). Almost Fare Free: Impact of a Cheap Public Transport Ticket on Mobility Patterns and Infrastructure Quality.

Loder, A., Cantner, F., Adenaw, L., Siewert, M. B., Goerg, S., and Bogenberger, K. (2023). A Nation-wide Experiment, Part II: The Introduction of a 49-Euro-per-month Travel Pass in Germany - An Empirical Study on this Fare Innovation. Preprint. Available at: https://arxiv.org/pdf/2305.04248.pdf (accessed: June 11, 2023).

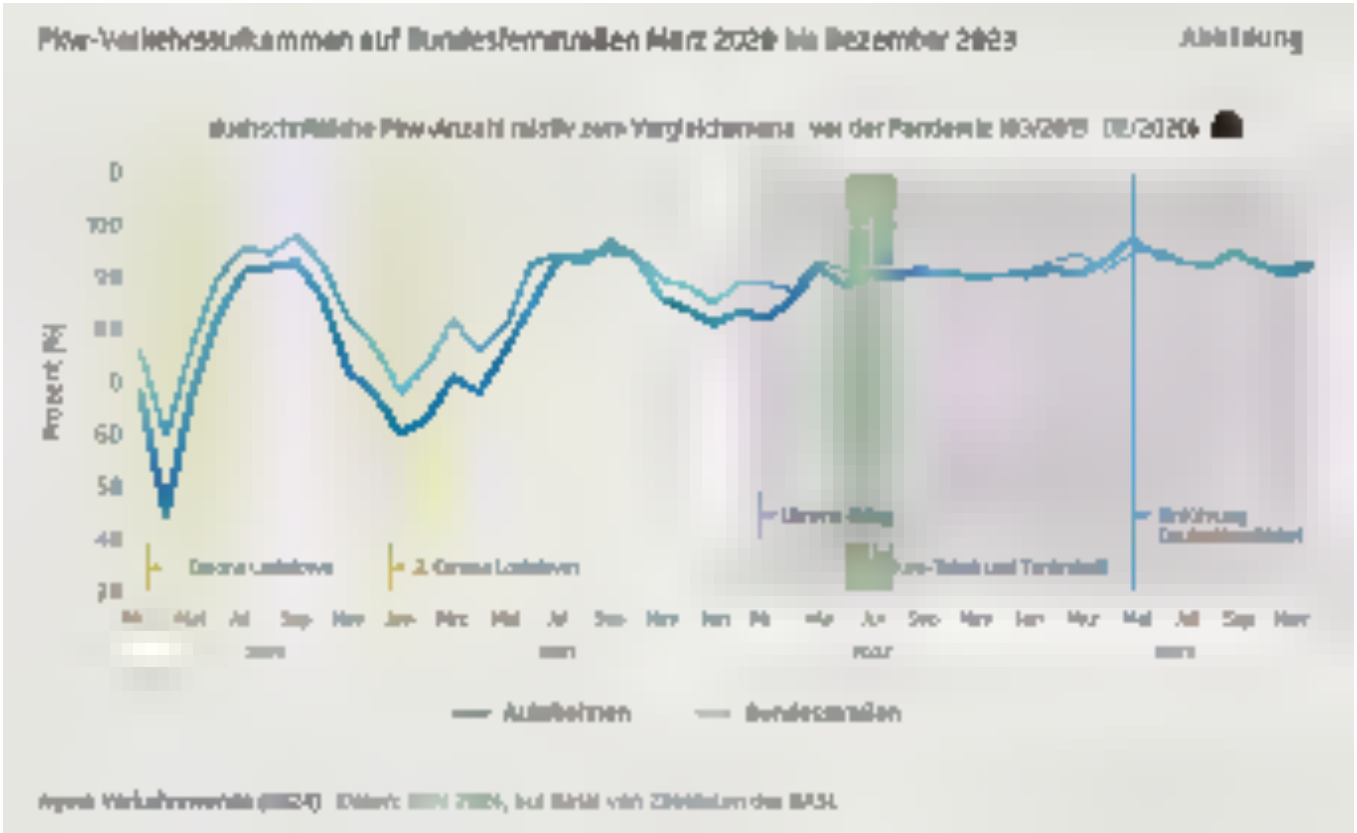
Statista (2021). Preise für Monatstickets des Öffentlichen Personennahverkehr (ÖPNV) in ausgewählten Städten Deutschlands. Available at: https://de.statista.com/statistik/daten/studie/1017765/umfrage/preise-fuer-monatstickets-des-oepnv-in-ausgewaehlten-staedten-deutschlands/ (accessed: June 18, 2023).

Tsivanidis, J. N. (2018). The Aggregate and Distributional Effects of Urban Transit Infrastructure: Evidence from Bogotá's TransMilenio. University of Chicago.

Wallimann, H., Blättler, K., and von Arx, W. (2023). Do Price Reductions Attract Customers in Urban Public Transport? A Synthetic Control Approach. *Transportation Research Part A: Policy and Practice*, 173:103700.

Data Credibility: Teralytics

- Data on road traffic is **consistent with BASt-data:**
  - **In 1st lockdown:** Reduction of up to 50%
  - **In 2nd lockdown:** Reduction of up to 40%

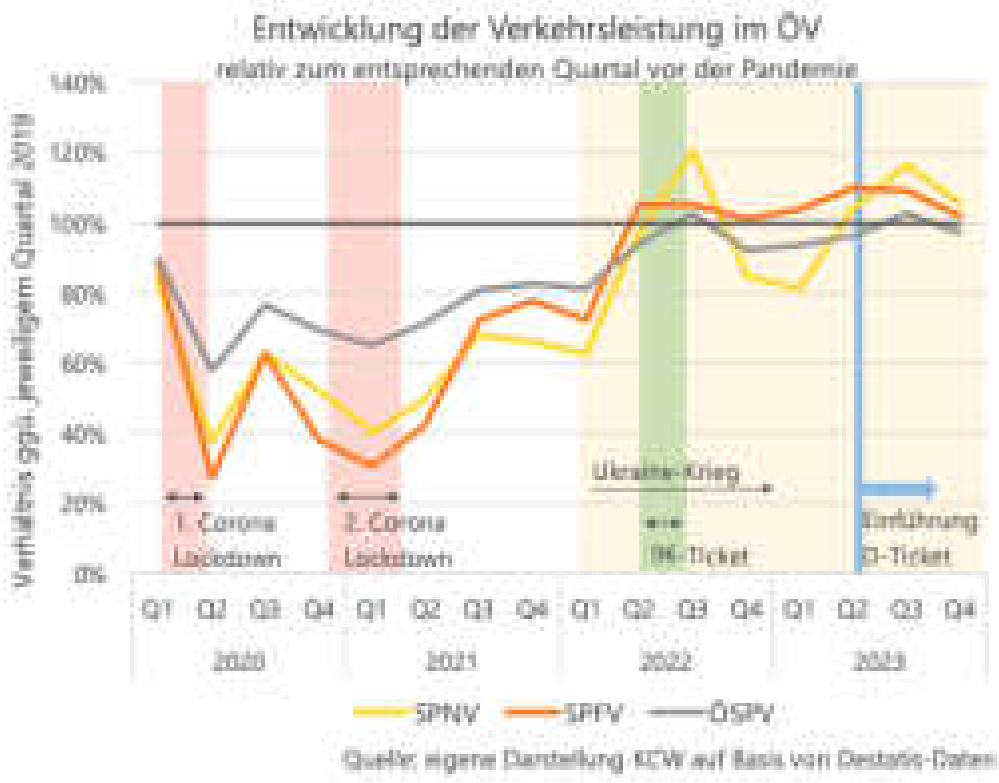


Source: Agora Verkehrswende (2024).

Back to data

Data Credibility: Teralytics

- Data on rail traffic is **consistent with Destatis-data:**
  - **In 1^{st} lockdown:** Reduction of up to 60-80%
  - **In 2^{nd} lockdown:** Reduction of up to 60-70%



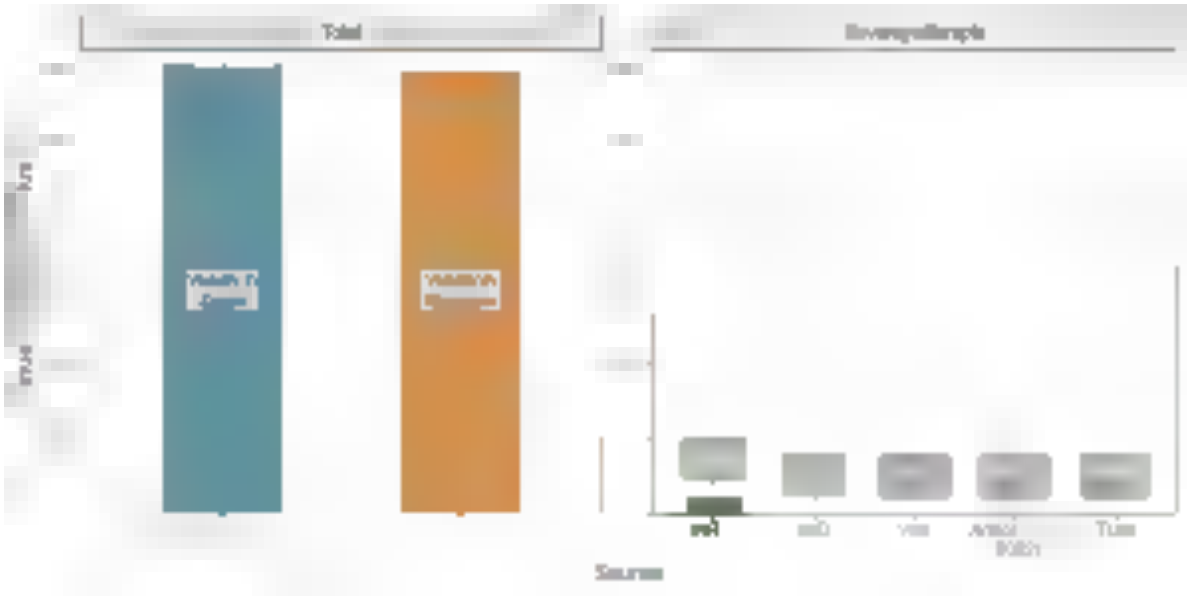
Source: KCW (2024).

Back to data

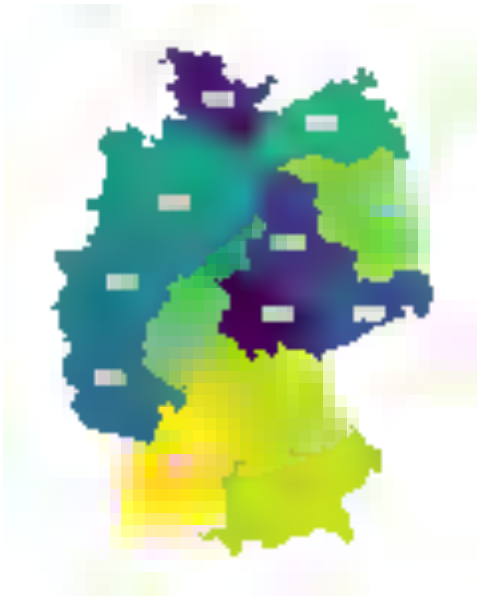
Data Coverage: INRIX

Annual Mileage in 2022

(a) Germany



(b) By regional state



Back to data

Identification Strategy

❌ **First (naive) idea:**

- **D**ifferences-**i**n-**D**ifferences **(DiD)** = uses a single untreated country or an unweighted average of untreated countries as control group

  ⇒ Unlikely that parallel trend assumption holds!

Identification Strategy

❌ First (naive) idea:

- **D**ifferences-**i**n-**D**ifferences **(DiD)** = uses a single untreated country or an unweighted average of untreated countries as control group
  - ⇒ Unlikely that parallel trend assumption holds!

💡 What if we don't have a good control group?

- Idea: synthesize one
  (Abadie and Gardeazabal, 2003; Abadie et al., 2010, 2015; Abadie, 2021)
  - ⇒ **S**ynthetic **C**ontrol **M**ethod **(SCM)** = builds a counterfactual of Germany using a weighted combination of carefully chosen non-treated countries or regions (denoted by 'synthetic Germany')
    - Formalizes the selection using a data-driven procedure

Identification Strategy

❌ First (naive) idea:

- **D**ifferences-**i**n-**D**ifferences **(DiD)** = uses a single untreated country or an unweighted average of untreated countries as control group
  - ⇒ Unlikely that parallel trend assumption holds!

💡 What if we don't have a good control group?

- Idea: synthesize one
  (Abadie and Gardeazabal, 2003; Abadie et al., 2010, 2015; Abadie, 2021)
  - ⇒ **S**ynthetic **C**ontrol **M**ethod **(SCM)** = builds a counterfactual of Germany using a weighted combination of carefully chosen non-treated countries or regions (denoted by 'synthetic Germany')
    - Formalizes the selection using a data-driven procedure
- If set of requirements fulfilled, **'synthetic Germany' resembles Germany** on key mobility predictors and has similar levels and paths of mobility volume

Standard SCM: general idea & concept

- **Requirements**:
  1. Countries in 'synthetic Germany' are **not affected** by Germany's €9-ticket nor have implemented **similar policies**
  2. The support of control units contains the **support** of treated unit
  3. A **weighting vector W** exists that minimizes distance (MSPE) between pre-treatment characteristics and outcome variable of the treated unit and synthetic units (over the pre-treatment period)
     - Get the efficient country weights (W) and weights for relatively more important predictors of the outcome variable (V) with a nested optimization program

Go to details on SCM setup

Standard SCM: general idea & concept

- **Requirements**:
  1. Countries in 'synthetic Germany' are **not affected** by Germany's €9-ticket nor have implemented **similar policies**
  2. The support of control units contains the **support** of treated unit
  3. A **weighting vector W** exists that minimizes distance (MSPE) between pre-treatment characteristics and outcome variable of the treated unit and synthetic units (over the pre-treatment period)
     - Get the efficient country weights (W) and weights for relatively more important predictors of the outcome variable (V) with a nested optimization program

Go to details on SCM setup

✅ If fulfilled, **'synthetic Germany' resembles Germany** on a number of key predictors of the mobility trend and has similar levels and paths of mobility volume

Standard SCM: general idea & concept

- **Requirements**:
  1. Countries in 'synthetic Germany' are **not affected** by Germany's €9-ticket nor have implemented **similar policies**
  2. The support of control units contains the **support** of treated unit
  3. A **weighting vector W** exists that minimizes distance (MSPE) between pre-treatment characteristics and outcome variable of the treated unit and synthetic units (over the pre-treatment period)
     - Get the efficient country weights (W) and weights for relatively more important predictors of the outcome variable (V) with a nested optimization program

Go to details on SCM setup

✅ If fulfilled, **'synthetic Germany' resembles Germany** on a number of key predictors of the mobility trend and has similar levels and paths of mobility volume

💡 However, weights often depend a lot on **choice of characteristics to be matched** (Ferman et al., 2020)

⇒ SC that uses all pre-treatments outcome periods is a good benchmark

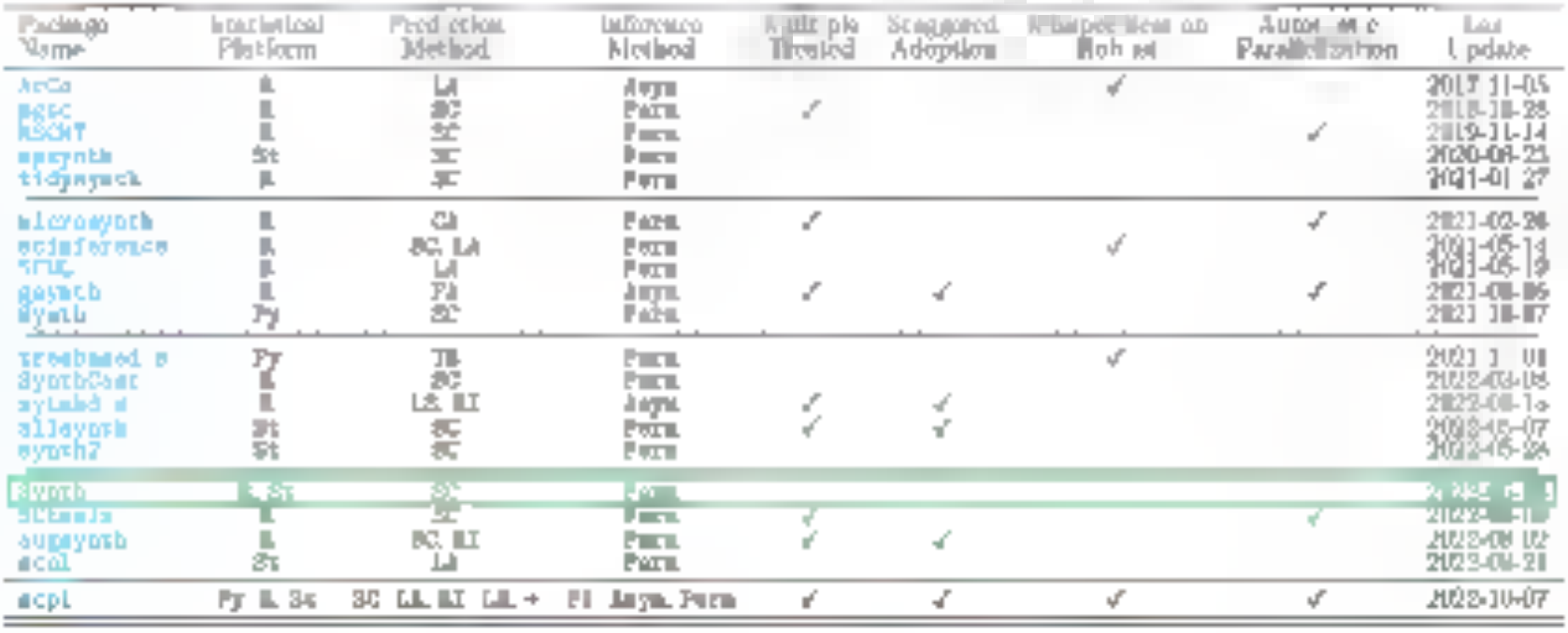
Go to details

Many improvements & extensions to the SCM in recent years

Package Name	Statistical Platform	Prediction Method	Inference Method	Multiple Treated	Staggered Adoption	Misspecification Robust	Automatic Parallelization	Last Update
[arCo]	R	LA	Asym			✓		2017-11-05
[gsc]	R	SC	Perm	✓				2018-10-28
[RSCIT]	R	SC	Perm				✓	2019-11-14
[apsynth]	St	SC	Perm					2020-06-23
[tidysynth]	R	SC	Perm					2021-01-27
[microsynth]	R	CA	Perm	✓			✓	2021-02-26
[scinference]	R	SC, LA	Perm			✓		2021-05-14
[scm]	R	LA	Perm					2021-05-19
[gsynth]	R	FA	Asym	✓	✓		✓	2021-08-16
[fsynth]	Py	SC	Perm					2021-10-07
[treebased-sc]	Py	TB	Perm			✓		2021-11-01
[SynthBasr]	R	SC	Perm					2022-03-08
[sytabdid]	R	LS, RI	Asym	✓	✓			2022-03-15
[allsynth]	St	SC	Perm	✓	✓			2022-05-07
[synth2]	St	SC	Perm					2022-05-28
[fsynth]	R, St	SC	Perm					2022-06-08
[SCtools]	R	SC	Perm	✓			✓	2022-06-09
[augsynth]	R	SC, RI	Perm	✓	✓			2022-06-02
[scul]	St	LA	Perm					2022-06-21
[scpi]	Py, R, St	SC, LS, RI, LS: +	PI, Asym, Perm	✓	✓	✓	✓	2022-10-07

Note: Py = Python (https://www.python.org/); R = R (https://cran.r-project.org/); St = Stata (https://www.stata.com/); LA = Lasso penalty; CA = calibration; FA = factor-augmented models; LS = unconstrained least squares; RI = Ridge penalty; SC = canonical synthetic control; TB = tree-based methods; + = user-specified options (see Table 3 below for more details); Perm = permutation-based inference; Asym = asymptotic-based inference; PI = prediction intervals (non-asymptotic probability guarantees). The symbol ✓ means that the feature is available. The last column reports the date of last update as of October 7, 2022.

Many improvements & extensions to the SCM in recent years



Package Name	Statistical Platform	Prediction Method	Inference Method	Multiple Treated	Staggered Adoption	Unbalanced Panels	Automatic Parallelization	Last Update
AzCo	R	LR	Asym			✓		2017-11-05
gsynth	R	MC	Perm	✓				2018-10-28
RSCM	R	SC	Perm				✓	2019-11-14
augsynth	St	MC	Perm					2020-04-23
tidysynth	R	MC	Perm					2021-01-27
microsynth	R	CB	Perm	✓			✓	2021-02-26
scinference	R	SC, LR	Perm			✓		2021-05-14
SCUL	R	LR	Perm					2021-05-19
gsynth	R	PR	Asym	✓	✓		✓	2021-08-06
Synth	Py	SC	Perm					2021-10-07
treebased s	Py	TB	Perm			✓		2021-11-01
SyntheSmat	R	MC	Perm					2022-04-08
sybmb s	R	LR, RI	Asym	✓	✓			2022-08-16
allsynth	St	MC	Perm	✓	✓			2022-05-07
synth2	St	MC	Perm					2022-05-24
Synth	St	MC	Perm					2022-08-11
SCtools	R	SC	Perm	✓			✓	2022-08-19
augsynth	R	MC, RI	Perm	✓	✓			2022-08-02
scul	St	LR	Perm					2022-04-21
scpi	Py R St	SC LR RI LR + PI	Asym Perm	✓	✓	✓	✓	2022-10-07

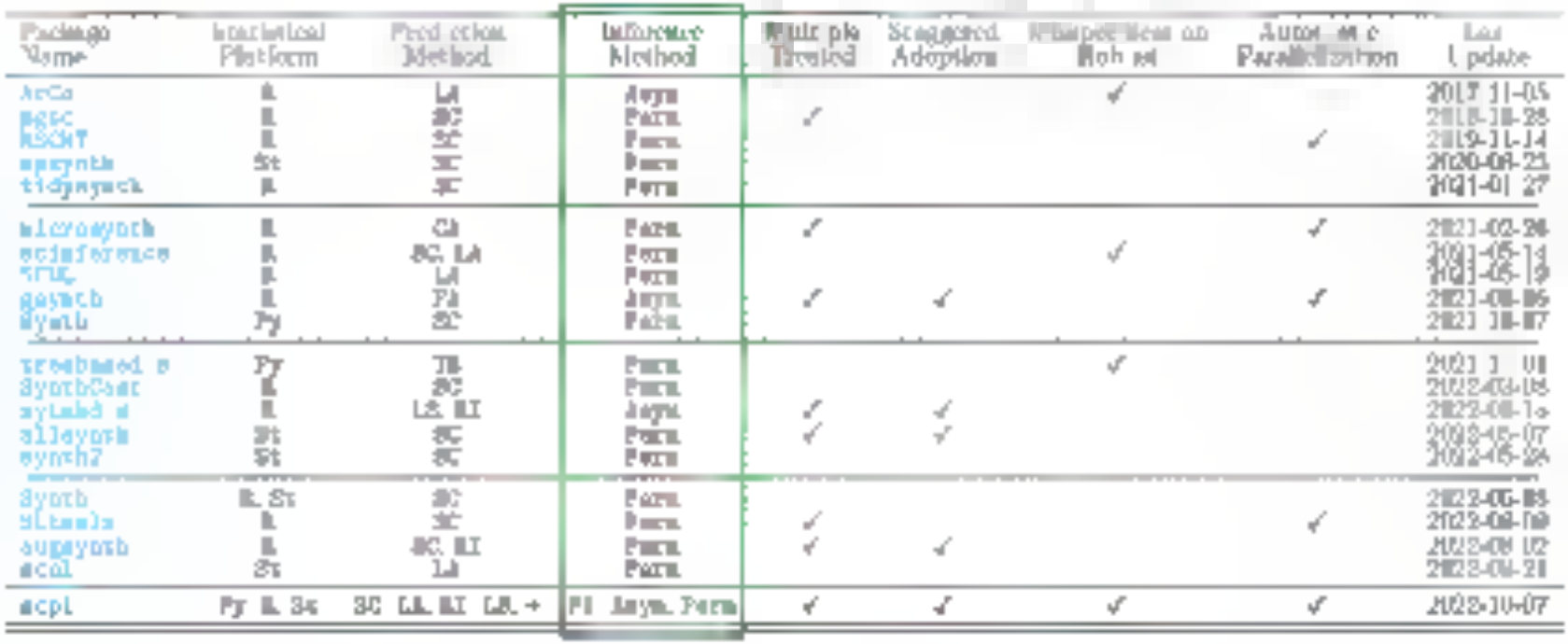
Note. Py = Python (https://www.python.org/) R = R (https://cran.r-project.org/) St = Stata (https://www.stata.com/) LR = Lasso penalty CB = calibration, PR = factor-augmented models LR = unconstrained least squares RI = Ridge penalty SC = canonical synthetic control TB = tree-based methods + = user-specified options (see Table 3 below for more details); Perm = permutation-based inference Asym = asymptotic-based inference PI = prediction intervals (non-asymptotic probability guarantees) The symbol ✓ means that the feature is available The last column reports the date of last update as of October 7 2022

Many improvements & extensions to the SCM in recent years

Package Name	Statistical Platform	Prediction Method	Inference Method	Multiple Treated	Staggered Adoption	Unbalanced Panels	Auto-matic Parallelization	Last Update
ArCo	R	LM	Asym			✓		2017-11-05
Mate	R	SC	Perm	✓				2018-10-28
RSCM7	R	SC	Perm				✓	2019-11-14
apsynth	St	SC	Perm					2020-04-23
tidysynth	R	SC	Perm					2021-01-27
microsynth	R	CB	Perm	✓			✓	2021-02-26
scinference	R	SC, LA	Perm			✓		2021-05-14
trtc	R	LM	Perm					2021-05-19
gsynth	R	FA	Asym	✓	✓		✓	2021-08-06
Synth	Py	SC	Perm					2021-10-07
treebased s	Py	TB	Perm			✓		2021-11-01
SynthChat	R	SC	Perm					2022-04-08
synbsd s	R	LS, RI	Asym	✓	✓			2022-08-16
allsynth	St	SC	Perm	✓	✓			2022-05-07
synth2	St	SC	Perm					2022-05-24
Synth	R, St	SC	Perm					2022-06-03
ditmala	R	SC	Perm	✓			✓	2022-08-10
augsynth	R	SC, RI	Perm	✓	✓			2022-08-02
scul	St	LA	Perm					2022-04-21
scpi	Py, R, St	SC, LS, RI, LS, +	PI, Asym, Perm	✓	✓	✓	✓	2022-10-07

Note: Py = Python (https://www.python.org/); R = R (https://cran.r-project.org/); St = Stata (https://www.stata.com/); LS = Lasso penalty; CB = calibration; FA = factor-augmented models; LM = unconstrained least squares; RI = Ridge penalty; SC = canonical synthetic control; TB = tree-based methods; + = user-specified options (see Table 3 below for more details); Perm = permutation-based inference; Asym = asymptotic-based inference; PI = prediction intervals (non-asymptotic probability guarantees). The symbol ✓ means that the feature is available. The last column reports the date of last update as of October 7, 2022.

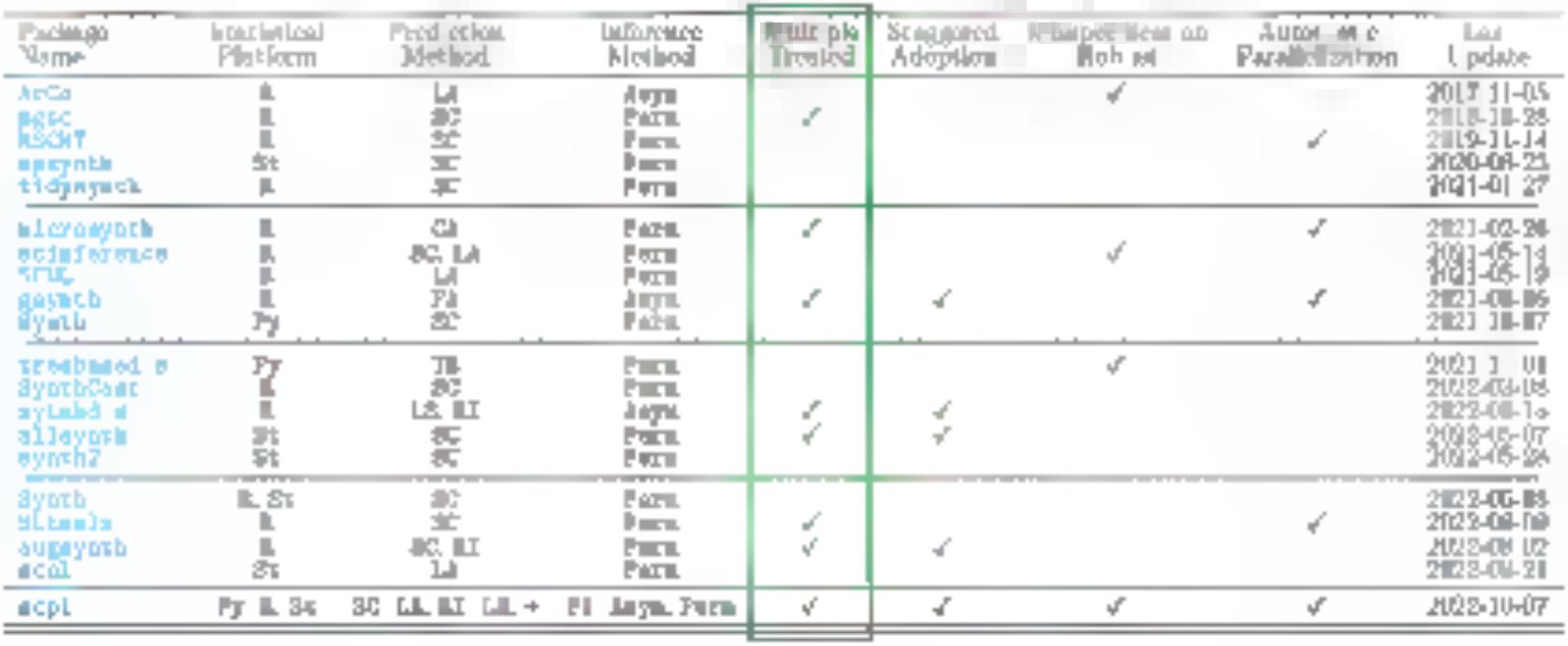
Many improvements & extensions to the SCM in recent years



Package Name	Statistical Platform	Prediction Method	Inference Method	Multiple Treated	Staggered Adoption	Multiple Outcomes	Automatic Parallelization	Last Update
ArCo	R	LR	Asym			✓		2017-11-05
gsynth	R	MC	Perm	✓				2018-10-28
RSCM	R	MC	Perm				✓	2019-11-14
augsynth	St	MC	Perm					2020-04-23
tidysynth	R	MC	Perm					2021-01-27
microsynth	R	CB	Perm	✓			✓	2021-02-26
scinference	R	MC, LR	Perm			✓		2021-05-14
SCUL	R	LR	Perm					2021-05-19
gsynth	R	PR	Asym	✓	✓		✓	2021-08-06
Synth	Py	MC	Perm					2021-10-07
treebased s	Py	TB	Perm			✓		2021-11-01
SyntheSmat	R	MC	Perm					2022-04-08
synbsd s	R	LR, RI	Asym	✓	✓			2022-08-16
allsynth	St	MC	Perm	✓	✓			2022-05-07
synth2	St	MC	Perm					2022-05-24
Synth	R, St	MC	Perm					2022-06-03
gltools	R	MC	Perm	✓			✓	2022-08-09
augsynth	R	MC, RI	Perm	✓	✓			2022-09-02
scul	St	LR	Perm					2022-09-21
scpi	Py, R, St	SC, LR, RI, LR, +	PI	Asym, Perm	✓	✓	✓	2022-10-07

Note: Py = Python (https://www.python.org/), R = R (https://cran.r-project.org/), St = Stata (https://www.stata.com/), LR = Lasso penalty, CB = calibration, FM = factor-augmented models, LR = unconstrained least squares, RI = Ridge penalty, SC = canonical synthetic control, TB = tree-based methods, + = user-specified options (see Table 3 below for more details); Perm = permutation-based inference, Asym = asymptotic-based inference, PI = prediction intervals (non-asymptotic probability guarantees). The symbol ✓ means that the feature is available. The last column reports the date of last update as of October 7, 2022.

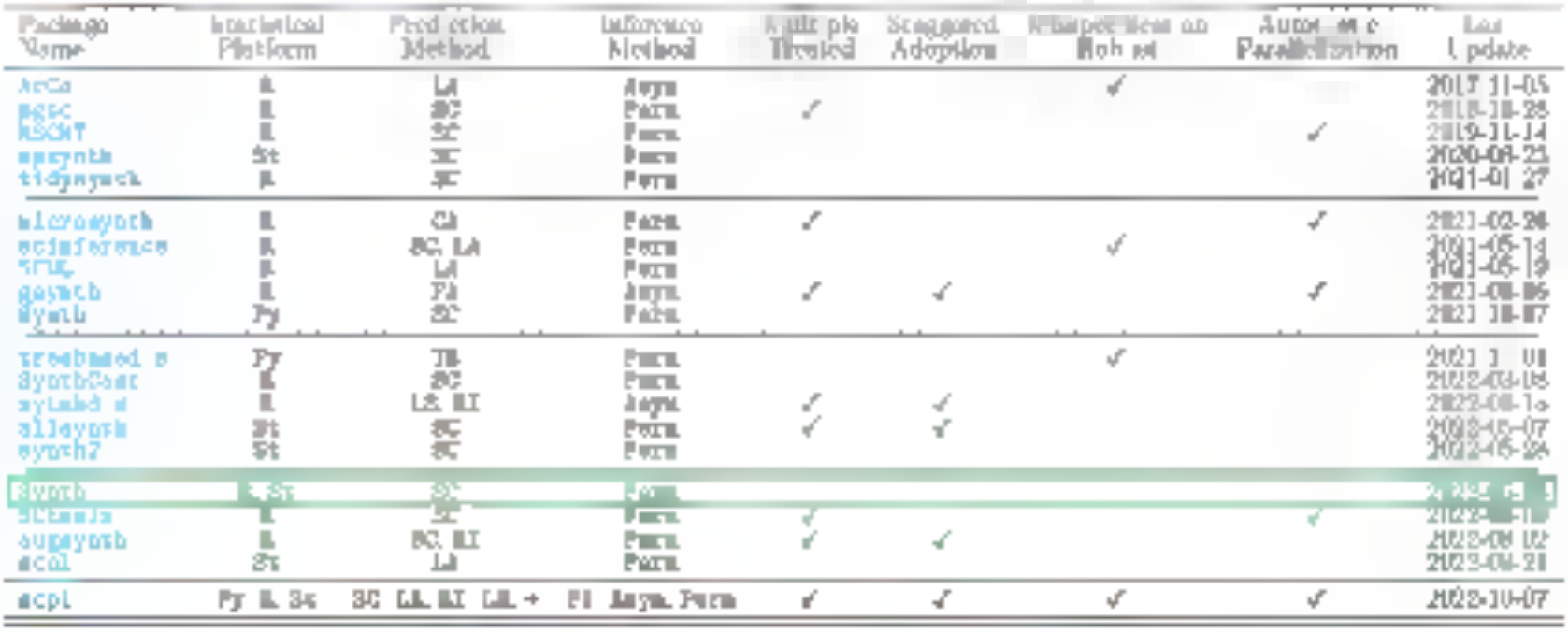
Many improvements & extensions to the SCM in recent years



Package Name	Statistical Platform	Prediction Method	Inference Method	Multiple Treated	Staggered Adoption	Unbalanced Panels or Non-stationarity	Automatic Parallelization	Last Update
AzCo	R	LR	Asym			✓		2017-11-05
gsynth	R	MC	Perm	✓				2018-10-28
RSCM7	R	SC	Perm				✓	2019-11-14
mgsynth	St	MC	Perm					2020-08-21
tidysynth	R	MC	Perm					2021-01-27
microsynth	R	CR	Perm	✓			✓	2021-02-26
scinference	R	SC, LR	Perm			✓		2021-05-14
trtf	R	LR	Perm					2021-05-19
gsynth	R	FE	Asym	✓	✓		✓	2021-08-06
Synth	Py	SC	Perm					2021-10-07
treebased s	Py	TB	Perm			✓		2021-11-01
SyntheSmat	R	SC	Perm					2022-04-08
sybmb s	R	LR, RI	Asym	✓	✓			2022-08-10
allsynth	St	MC	Perm	✓	✓			2022-05-07
synth2	St	MC	Perm					2022-05-24
Synth	R, St	SC	Perm					2022-06-03
gltools	R	MC	Perm	✓			✓	2022-08-10
augsynth	R	MC, RI	Perm	✓	✓			2022-09-02
scul	St	LR	Perm					2022-09-21
scpi	Py, R, St	SC	LR, RI	LR, +	PI	Asym, Perm	✓	2022-10-07

Note. Py = Python (https://www.python.org/) R = R (https://cran.r-project.org/) St = Stata (https://www.stata.com/) LR = Lasso penalty CR = calibration, FE = factor-augmented models LR = unconstrained least squares RI = Ridge penalty SC = canonical synthetic control TB = tree-based methods + = user-specified options (see Table 3 below for more details); Perm = permutation-based inference Asym = asymptotic-based inference PI = prediction intervals (non-asymptotic probability guarantees) The symbol ✓ means that the feature is available The last column reports the date of last update as of October 7, 2022

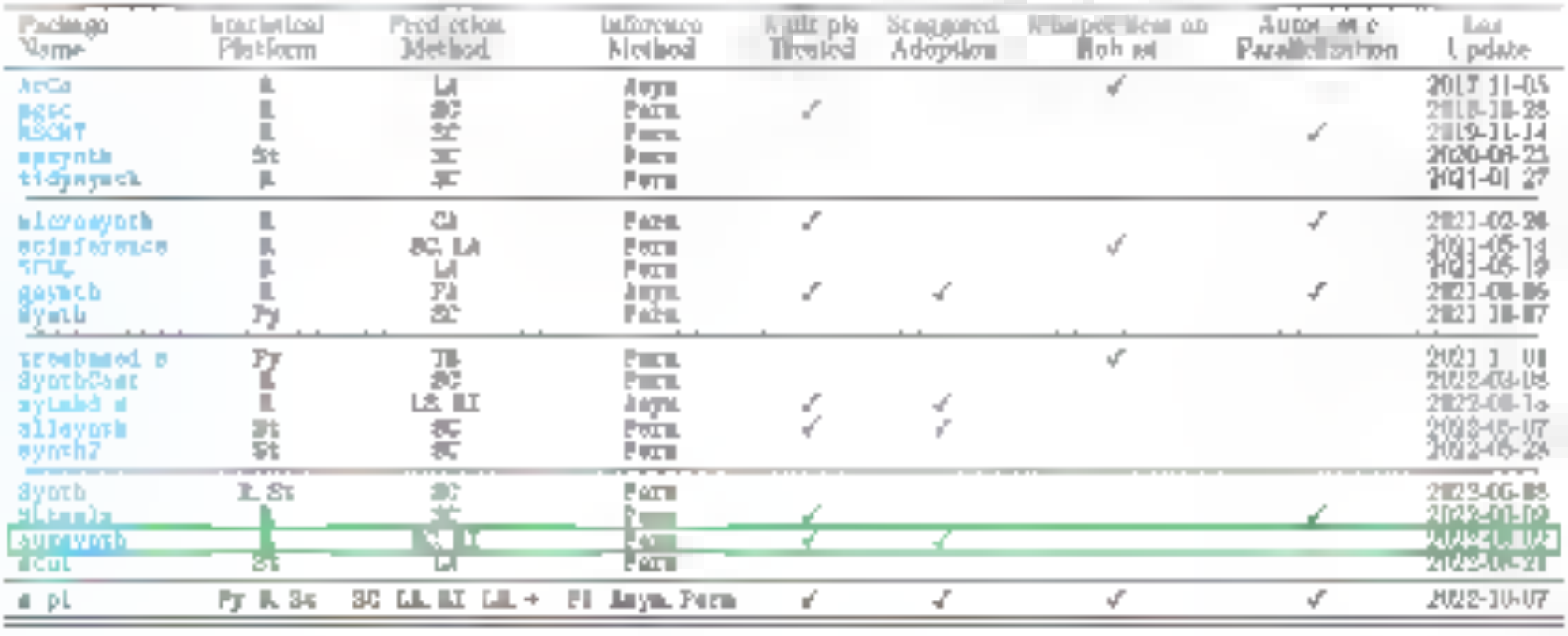
Many improvements & extensions to the SCM in recent years



Package Name	Statistical Platform	Prediction Method	Inference Method	Multiple Treated	Staggered Adoption	Unbalanced Panels	Automatic Parallelization	Last Update
AzCo	R	LR	Asym			✓		2017-11-05
gsynth	R	MC	Perm	✓				2018-10-28
RSCM	R	SC	Perm				✓	2019-11-14
augsynth	St	MC	Perm					2020-04-23
tidysynth	R	MC	Perm					2021-01-27
microsynth	R	CB	Perm	✓			✓	2021-02-26
scinference	R	SC, LR	Perm			✓		2021-05-14
SCUL	R	LR	Perm					2021-05-19
gsynth	R	PR	Asym	✓	✓		✓	2021-08-06
Synth	Py	SC	Perm					2021-10-07
treebased s	Py	TB	Perm			✓		2021-11-01
SyntheSmat	R	MC	Perm					2022-04-08
sybmb s	R	LR, RI	Asym	✓	✓			2022-08-16
allsynth	St	MC	Perm	✓	✓			2022-05-07
synth2	St	MC	Perm					2022-05-24
Synth	St	MC	Perm					2022-08-11
SCtools	R	SC	Perm	✓			✓	2022-08-19
augsynth	R	MC, RI	Perm	✓	✓			2022-08-02
scul	St	LR	Perm					2022-04-21
scpi	Py R St	SC LR RI LR + PI	Asym Perm	✓	✓	✓	✓	2022-10-07

Note. Py = Python (https://www.python.org/) R = R (https://cran.r-project.org/) St = Stata (https://www.stata.com/) LR = Lasso penalty CB = calibration, PR = factor-augmented models LR = unconstrained least squares RI = Ridge penalty SC = canonical synthetic control TB = tree-based methods + = user-specified options (see Table 3 below for more details); Perm = permutation-based inference Asym = asymptotic-based inference PI = prediction intervals (non-asymptotic probability guarantees) The symbol ✓ means that the feature is available The last column reports the date of last update as of October 7 2022

Many improvements & extensions to the SCM in recent years



Package Name	Statistical Platform	Prediction Method	Inference Method	Multiple Treated	Staggered Adoption	Unbalanced Panels OK	Automatic Parallelization	Last Update
AzCo	R	LR	Asym			✓		2017-11-05
gsynth	R	MC	Perm	✓				2018-10-28
RSCM	R	SC	Perm				✓	2019-11-14
augsynth	St	MC	Perm					2020-04-23
tidysynth	R	MC	Perm					2021-01-27
microsynth	R	CB	Perm	✓			✓	2021-02-26
scinference	R	SC, LR	Perm			✓		2021-05-14
SCUL	R	LR	Perm					2021-05-19
gsynth	R	PS	Asym	✓	✓		✓	2021-08-06
Synth	Py	SC	Perm					2021-10-07
treebased s	Py	TB	Perm			✓		2021-11-01
SyntheSmat	R	MC	Perm					2022-04-08
sybmb s	R	LR, RI	Asym	✓	✓			2022-08-16
allsynth	St	MC	Perm	✓	✓			2022-05-07
synth2	St	MC	Perm					2022-05-24
Synth	R, St	MC	Perm					2022-06-05
mltsynth	R	MC	Perm	✓			✓	2022-09-09
augsynth	R	MC, RI	Perm	✓	✓			2022-09-09
scul	St	LR	Perm					2022-09-21
s pl	Py R, St	MC LR, RI LR, +	PI Asym, Perm	✓	✓	✓	✓	2022-10-07

Note. Py = Python (https://www.python.org/) R = R (https://cran.r-project.org/) St = Stata (https://www.stata.com/) LR = Lasso penalty CB = calibration, FA = factor-augmented models LR = unconstrained least squares RI = Ridge penalty MC = canonical synthetic control TB = tree-based methods + = user-specified options (see Table 3 below for more details); Perm = permutation-based inference Asym = asymptotic-based inference PI = prediction intervals (non-asymptotic probability guarantees) The symbol ✓ means that the feature is available The last column reports the date of last update as of October 7, 2022

Potential Predictors for Optimization

- **Key country-level predictors** of mobility behavior (in 2019)
  - Log GDP per capita (in PPS)
  - Modal split
    - Share of train (in %)
    - Share of bus (in %)
  - Available infrastructure
    - Rail density (km per 100 km^2)
    - Road density (km per 100 km^2)
  - Urban population (in %)
  - Working age population (in %)
  - Impressionable years population (in %)
  - ...

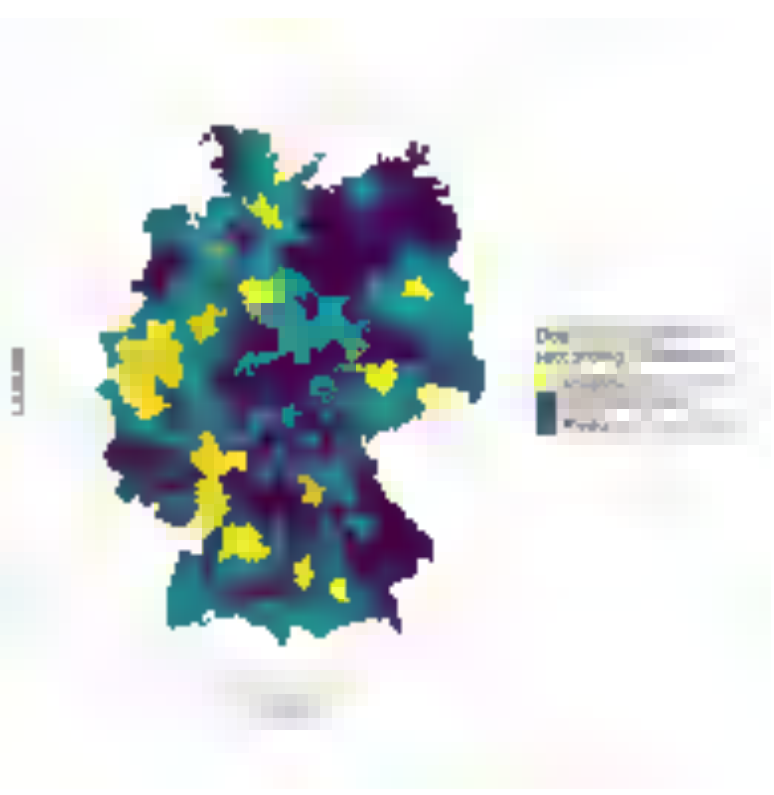
However, weights often depend a lot on **choice of characteristics to be matched** (Ferman et al., 2020)

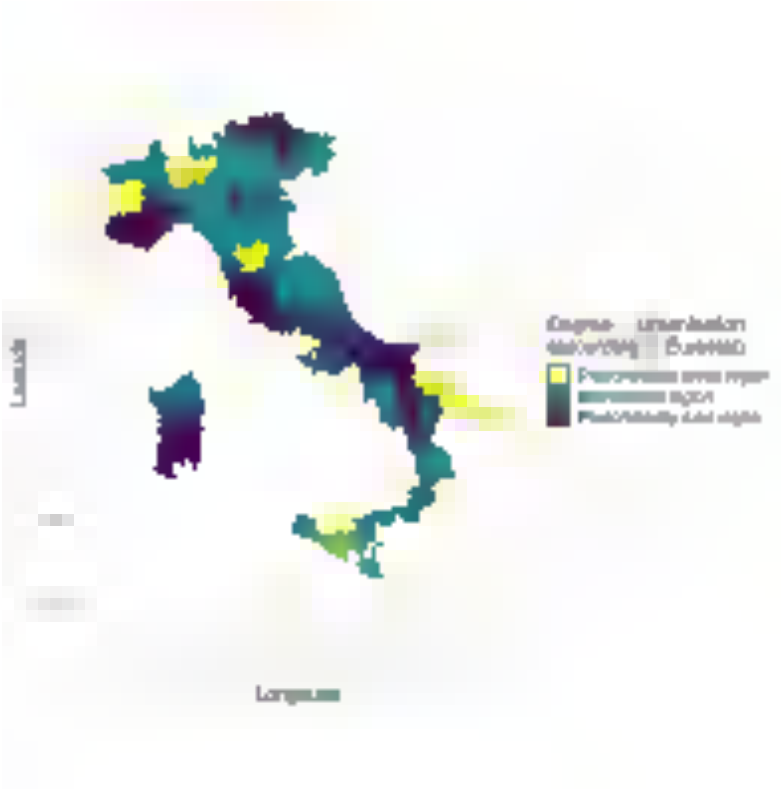
$\Rightarrow$ SC that uses all pre-treatments periods is a good benchmark

Back to general idea

Potential Covariates to Match on

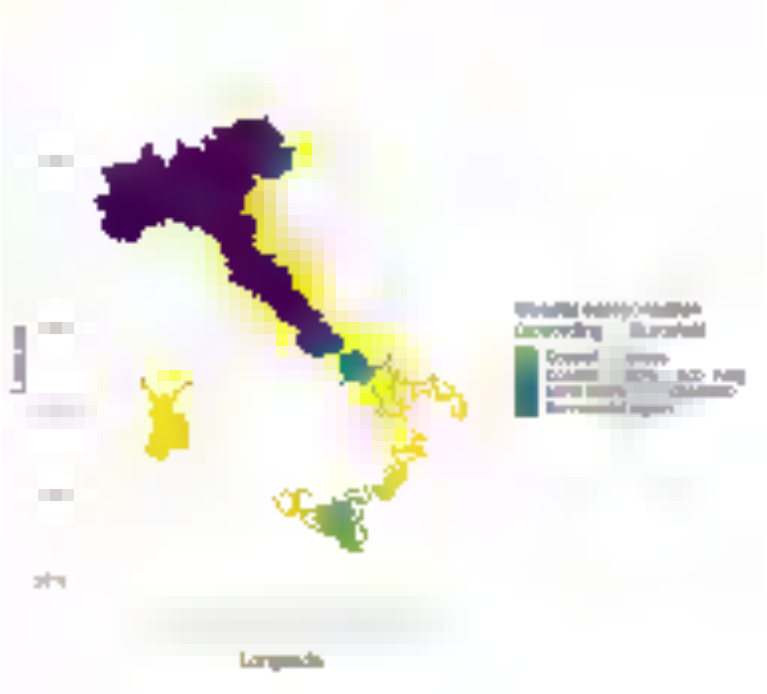
Degree of urbanization





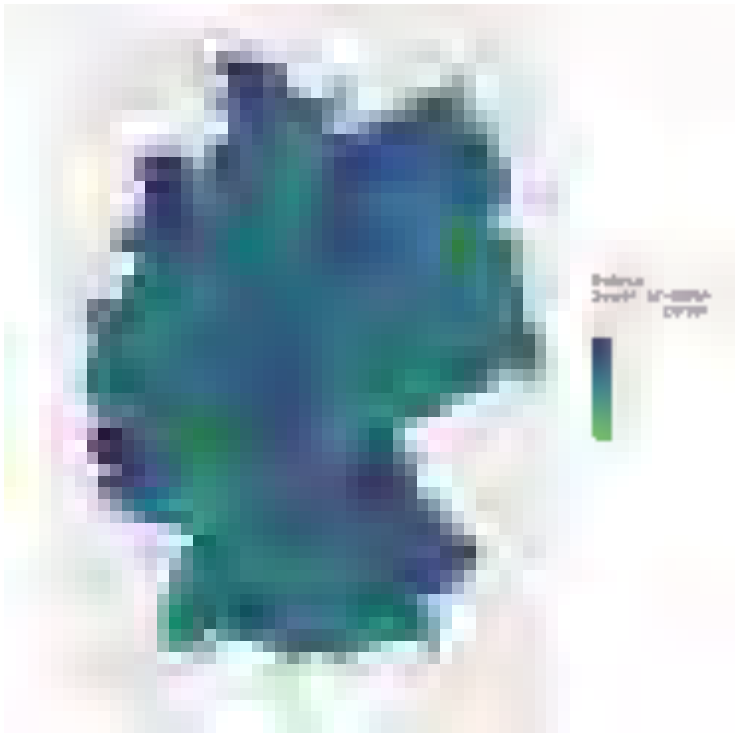
Potential Covariates to Match on

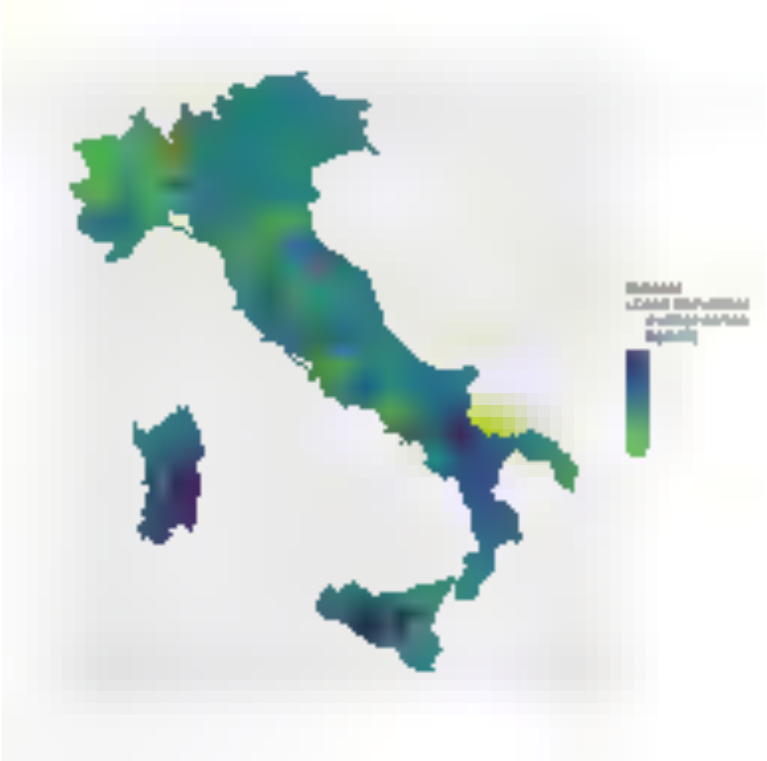
Touristic/coastal regions



Potential Covariates to Match on

Quality of PT connection





Augmented SCM

- **Standard SCM approach:** SC weights need to be non-negative and sum to one **(simplex constraint)**
  - Main advantage: Intuitive and straightforward interpretation of estimates
  - **BUT:** In many settings simplex constraint on the weights prevents sufficiently close pre-treatment fit due to the curse of dimensionality

Augmented SCM

- **Standard SCM approach:** SC weights need to be non-negative and sum to one **(simplex constraint)**
  - Main advantage: Intuitive and straightforward interpretation of estimates
  - **BUT:** In many settings simplex constraint on the weights prevents sufficiently close pre-treatment fit due to the curse of dimensionality
- **Augmented SCM approach** proposed by Ben-Michael et al. (2021) extends the traditional SCM by relaxing the constraint and correcting bias from a non-optimal pre-treatment fit
  - How: Integration of an outcome model based on ridge regression
  - Here: Use all pre-treatments outcome periods as predictors (Ferman et al., 2020)
- Applied in case of country-level data (INRIX)

Back to implementation details

Partially Pooled SCM

- Traditional SCM was developed for single treated units but approach is adapted to the context of **multiple treated units**
  - ⇒ **BUT:** Common approaches (see, e.g., Dube and Zipperer, 2015; Donohue et al., 2019; Abadie and L'Hour, 2021) only work well, if a sufficiently good SC for each treated unit is achieved

Partially Pooled SCM

- Traditional SCM was developed for single treated units but approach is adapted to the context of **multiple treated units**
  - ⇒ **BUT:** Common approaches (see, e.g., Dube and Zipperer, 2015; Donohue et al., 2019; Abadie and L'Hour, 2021) only work well, if a sufficiently good SC for each treated unit is achieved

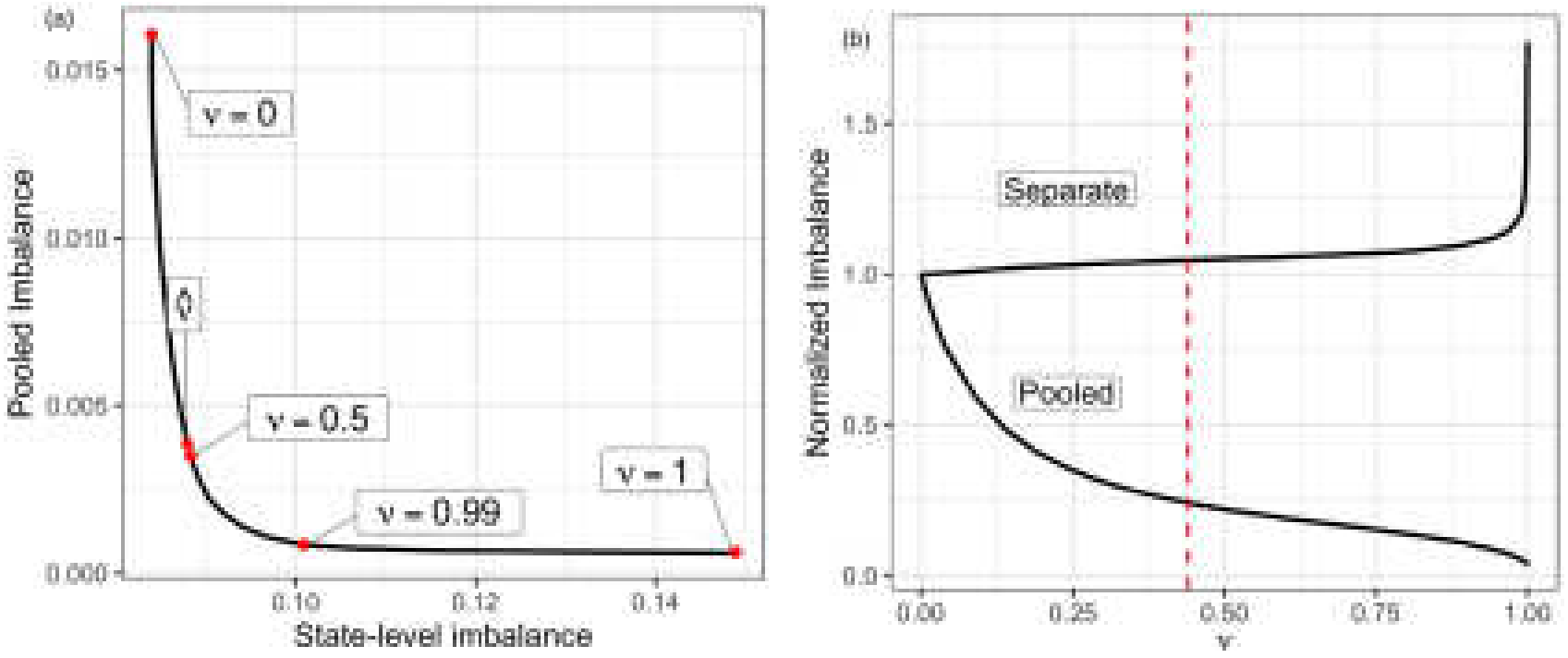
- **"Partially pooled" SCM** is a recent extension proposed by Ben-Michael et al. (2022) seeking to minimize a weighted average of two sources of pre-treatment imbalance:
  1. Unit-specific imbalance for each treated unit **(extreme with separate SC)**
  2. Imbalance for the treated units' average **(extreme with a pooled SC)**
  - ⇒ **Hyperparameter** ν governs the relative importance of the two balance objectives (trade-off) by smoothly transitioning between the two extremes

Graphical illustration

- Applied in the case of region-level data (Teralytics)

Back to implementation details

Ben-Michael et al. (2022): Hyperparameter ν



Notes: (a) The trade-off between pooled imbalance and unit-specific imbalance as ν varies, where $\nu = 0$ is the separate SCM solution and $\nu = 1$ is the pooled SCM solution. (b) Pooled imbalance and unit-specific imbalance versus ν, each normalized by their values for separate SCM. The dashed red line indicates $\hat{\nu}$. *Source:* Ben-Michael et al. (2022).

Back

Elasticity of Demand for PT (Back-of-the-envelope)

- **€49-ticket** decreased monthly ticket prices by about 40%
  - ⇒ Demand for PT increased by about 30.4%

$$\epsilon_{D-Ticket} = \frac{\%\Delta Q}{\%\Delta P} = \frac{30.4}{-40} = \textbf{-0.76}$$

- **€9-ticket** decreased monthly ticket prices by almost 90%
  - ⇒ Demand for PT increased by about 53.4%

$$\epsilon_{€9-Ticket} = \frac{\%\Delta Q}{\%\Delta P} = \frac{53.4}{-90} = \textbf{-0.59}$$

- **Interpretation:** In both cases, $\epsilon_D < 1$
  - ⇒ Elasticity is more than 1.3 times higher for permanent €49-ticket
  - ⇒ Similar to findings for role of persistence and salience in tax literature (Li et al., 2014; Andersson, 2019)

Back to results

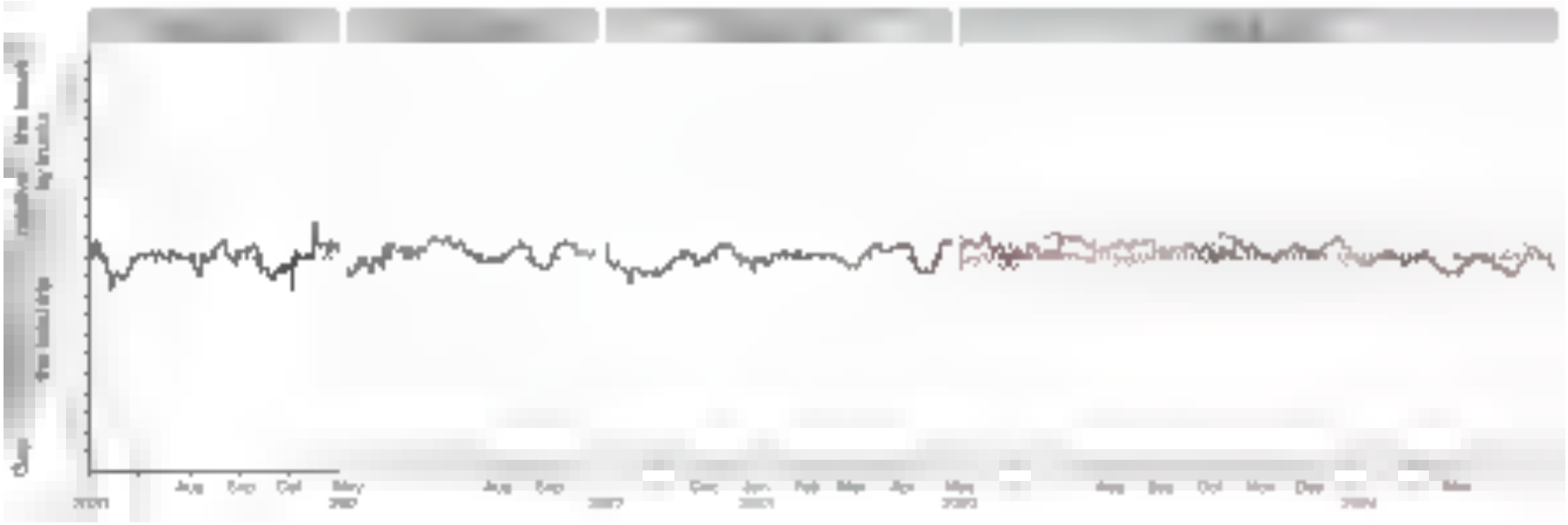
Question:
Do we see a change in the use of trucks?

Intensive Margin: km traveled

INRIX

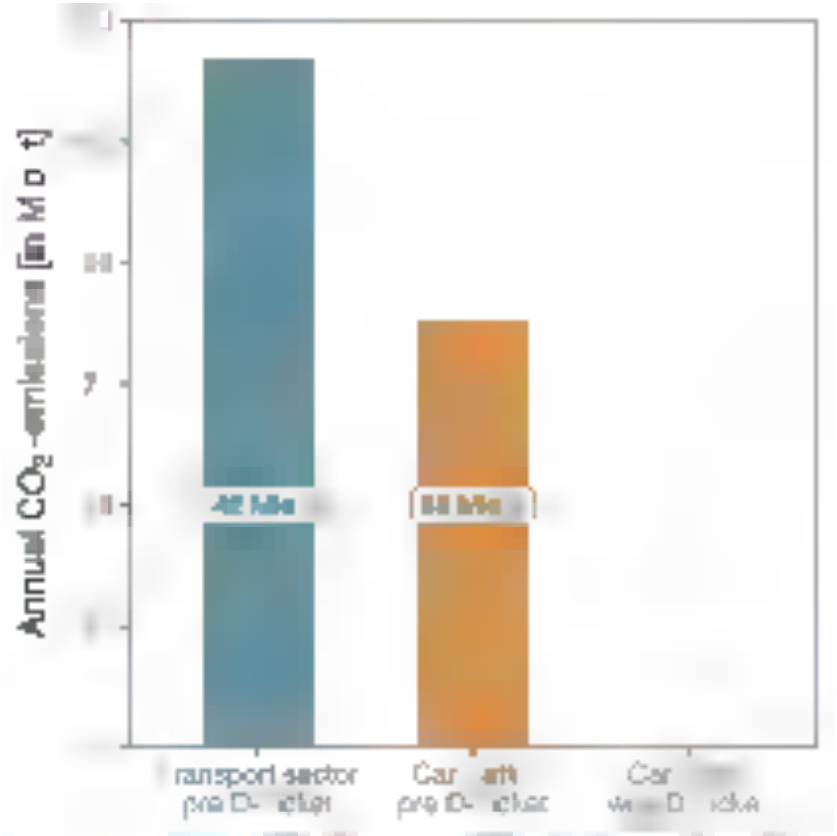
- Based on GPS signals from connected vehicles
- 🇩🇪 and 🇪🇺+
  - ⇒ National level
  - ⇒ Augmented SCM

Placebo Test: Trucks



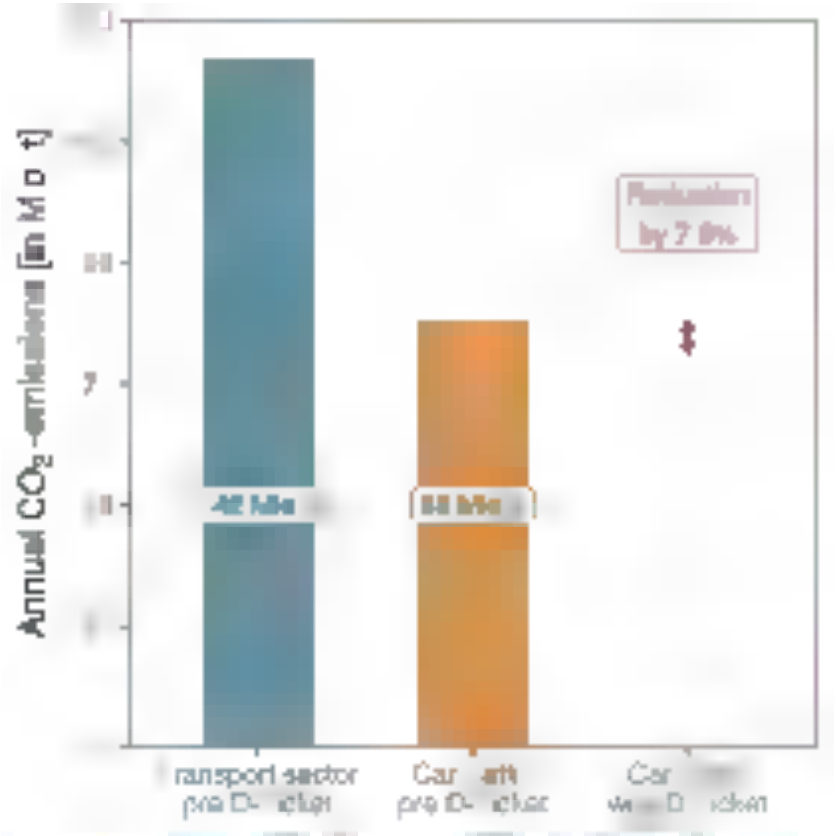
Back to main results

How Large is the Emission Reduction?



Back to Ariadne D-Ticket Impact Tracker

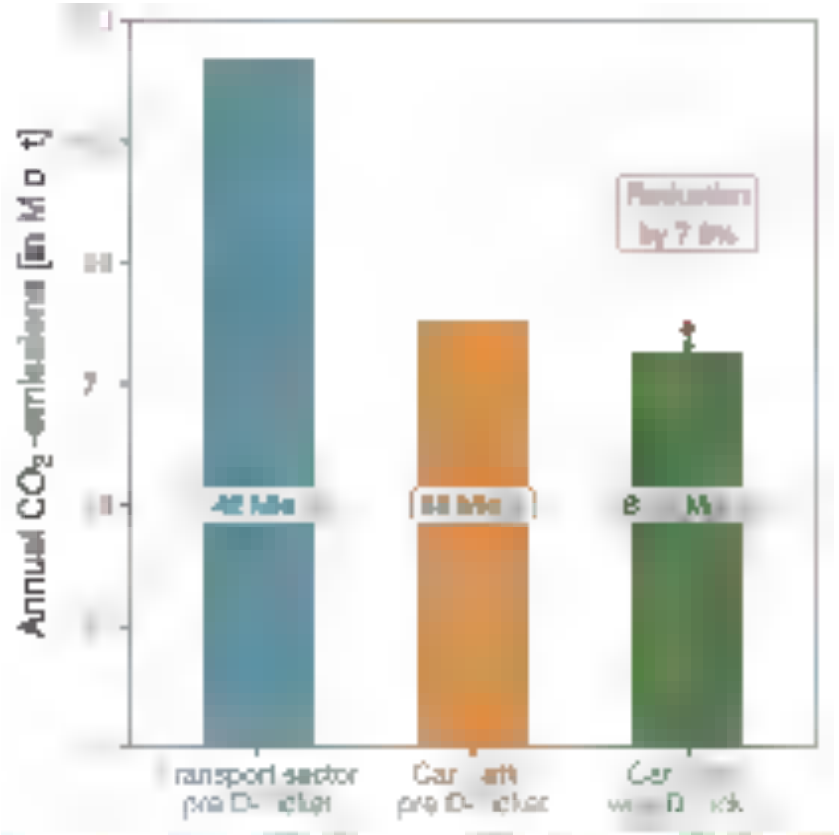
How Large is the Emission Reduction?



- Calculated based on estimated reduction of car kilometers driven

Back to Ariadne D-Ticket Impact Tracker

How Large is the Emission Reduction?



- Calculated based on estimated reduction of car kilometers driven
- **Emission reduction of 6.7 million t CO_2**
  or
  4.7% of the transport sector's total emissions

Back to Ariadne D-Ticket Impact Tracker

What Does the Price Increase from €49 to €58 Imply?

To estimate the impact, we focus on **how citizens reacted to past price changes**:

- Specifically, we use the **introduction of the D-Ticket** as our "experiment"
  (significant price reduction of about 40%)
  - **Increase in PT demand** by 30.4%
    Price elasticity: $\epsilon_{D-Ticket} = \frac{\%\Delta Q}{\%\Delta P} = \frac{30.4}{-40} = -0.76$
  - **Reduction in car kilometers driven** by 7.6%
    Cross-price elasticity: $\kappa_{D-Ticket} = \frac{\%\Delta Q}{\%\Delta P} = \frac{7.6}{-40} = 0.19$

$\Rightarrow$ **Simply put:** the past teaches us how strongly individuals increased their PT usage and reduced their car usage after a substantial price reduction.

What Does the Price Increase from €49 to €58 Imply?

To estimate the impact, we focus on **how citizens reacted to past price changes**:

- Specifically, we use the **introduction of the D-Ticket** as our "experiment"
  (significant price reduction of about 40%)
  - **Increase in PT demand** by 30.4%
    Price elasticity: $\epsilon_{D-Ticket} = \frac{\%\Delta Q}{\%\Delta P} = \frac{30.4}{-40} = -0.76$
  - **Reduction in car kilometers driven** by 7.6%
    Cross-price elasticity: $\kappa_{D-Ticket} = \frac{\%\Delta Q}{\%\Delta P} = \frac{7.6}{-40} = 0.19$

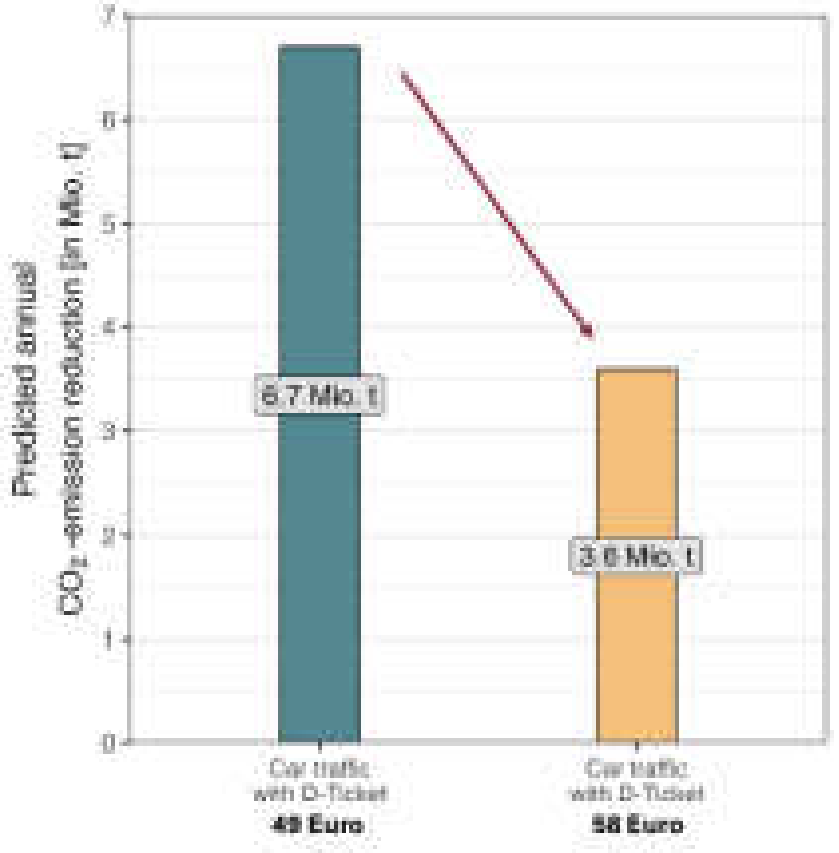
$\Rightarrow$ **Simply put:** the past teaches us how strongly individuals increased their PT usage and reduced their car usage after a substantial price reduction.

To forecast the impact of the price increase (by $\approx$18.4%), we **reverse the relationship learned from the past**:

- **Involved assumptions:**
  1. What held in the past, will also hold in the future
  2. Linear elasiticities (no "pain points")
  3. Symmetric elasticities

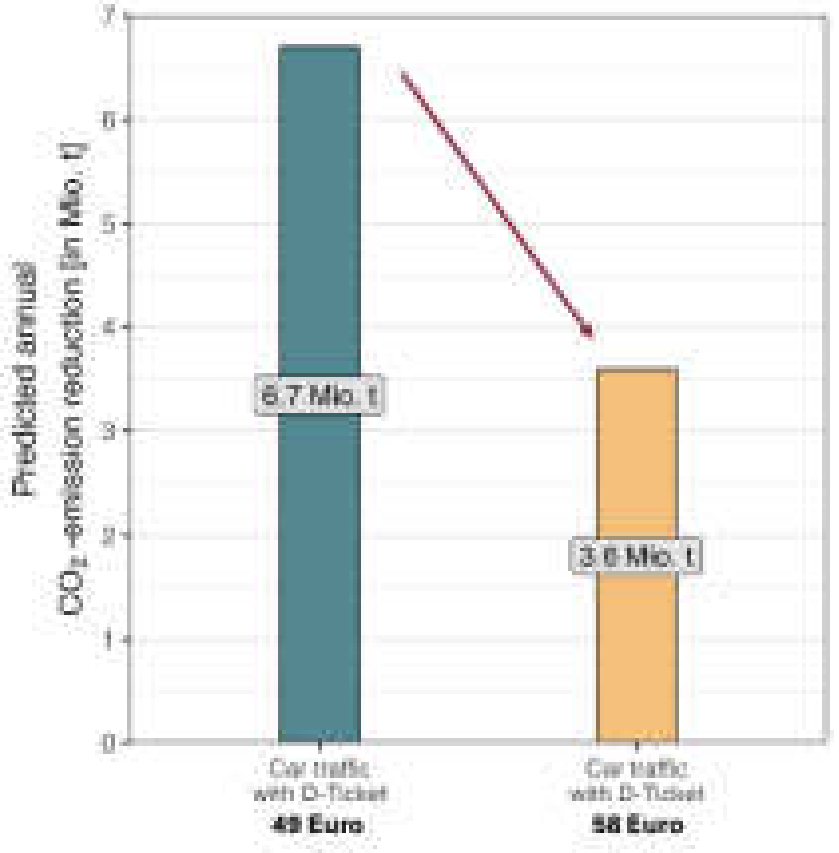
What does the price increase from €49 to €58 imply?

1. Reduction in PT demand by 14%
2. Increase in car kilometers driven by 3.5%
3. Increase in CO_2-emissions by 3.1 million t



What does the price increase from €49 to €58 imply?

1. Reduction in PT demand by 14%
2. Increase in car kilometers driven by 3.5%
3. Increase in CO_2-emissions by 3.1 million t



⇒ The price increase could almost **halve the annual emission savings achieved so far!**

Back to Ariadne D-Ticket Impact Tracker