# Zero fare, cleaner air? The causal effect of Luxembourg's free public transportation policy on carbon emissions

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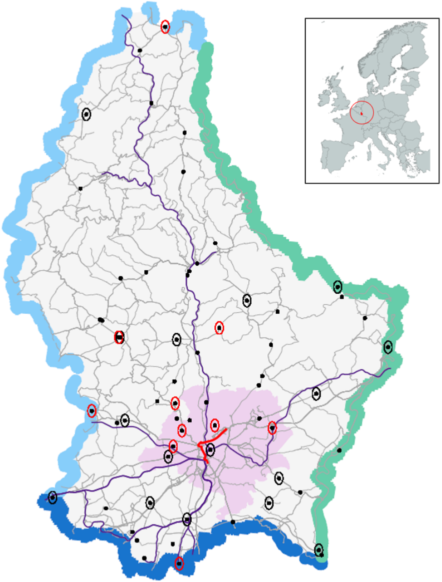
# Introduction

- In March 2020, Luxembourg became the first country to implement ***free public transport for everybody across all modes***

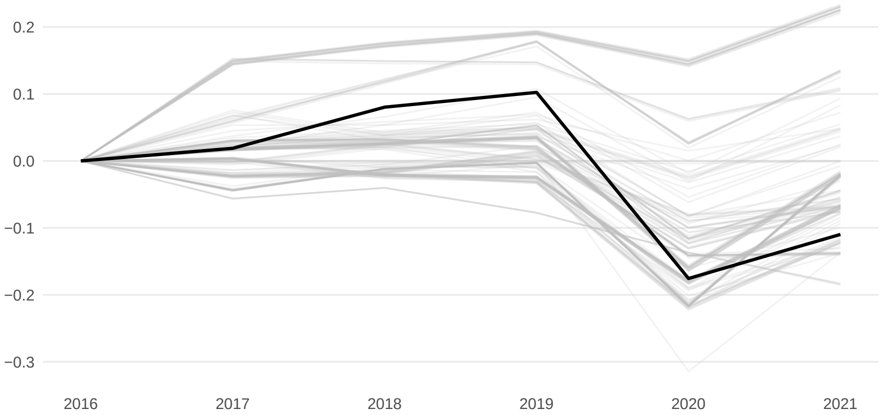
  $\longrightarrow$ Intention: reduce car density and associated negative externalities

- **RQ:** What are the effects of this policy on transport CO2 emissions?
- Identification challenges:
  1. Luxembourg is special
  2. COVID-19 - and associated variation in mobility patterns
- Data on CO2 emissions: IPCC-sector 1.A.3.b Grided CO2 emission data from EDGAR
- Unit of analysis: NUTS 2 level
- Method: Synthetic Difference in Differences (SDID) (Arkhangelsky et al., 2021)
- **Results**: ATT of around $-8\%$ CO2 road transport emissions

# Public Transport in Luxembourg



# Evolution of road transport emissions from LU




▸ spatial

# Luxembourg is special

- Size: 2,586.4 $km^2$
- Population: $\approx$ 660,000
- GDP/capita: $\approx$ 140,000 USD (highest in EU)
- Car density: $\approx$ 700 cars per 1,000 inhabitants (highest in EU)

**Challenge**:

- difficult to meet the parallel trend assumption for DiD
- SC assumes comparable pre-treatment levels

**Solution**:

- Unit of analysis: NUTS 2 level
- Use SDID, which combines characteristics of both SC and DID. Advantage: Does not assume comparable levels in any stage

# Potential Confounding

**Main threat: COVID-19**

Has mobility behavior in LU changed differently compared to other regions?

- COVID-19 cases ▸ details
- Commuting ▸ details
- Working from home ▸ details

**Other threats**

- Fuel prices, energy efficiency of new vehicles, freight volume

**Consider bad comparisons and spillovers** ▸ details

# Synthetic DiD

We apply syhthetic DiD to **emissions adjusted** for covariates ▸ details

**Synthetic DiD** combines features of both DiD and SC methods.

- Like DiD, it is invariant to additive unit-level shifts
- Like SC, it weighs and matches pre-treatment trends to reduce reliance on parallel-trends assumption

Synthetic DiD re-weighs **both units and time periods.** ▸ details

- Unit weights to match pre-treatment trends between exposed and unexposed units.
- Time weights assign higher weights to pre-treatment time periods that are more similar to post-treatment time periods for unexposed units.

## Placebo Inference

$\widehat{\tau}^{sdid}$ is asymptotically normal $\longrightarrow$ conventional CIs can be used if the asymptotic variance can be consistently estimated. $\tau \in \widehat{\tau}^{sdid} \pm z_{\alpha/2}\sqrt{\widehat{V}_\tau}$.

With $N_{tr} = 1$, we can use **placebo based inference**:

- Replace the exposed unit with unexposed units
- Randomly assign those units to a placebo treatment
- Compute a placebo ATT
- Repeat many times to obtain a vector of placebo ATTs

**Event-study inference** can be conducted by estimating:

$$d_t = (\bar{Y}_t^1 - \bar{Y}_t^0) - (\bar{Y}_{base}^1 - \bar{Y}_{base}^0).$$

Confidence bands around these estimates can be generated with a placebo-based approach (Arkhangelsky et al., 2021; Clarke et al., 2023). es-placebo

# Handling covariates

Handling covariates in this setting is treated as a **pre-modelling approach**. Model with fixed effects is estimated only for **control regions** as suggested by Kranz (2022):

$$Y_{it}^{co} = \alpha_i + \gamma_t + X_{it}^{co}\beta + u_{it}, \tag{1}$$

$$\widehat{Y}_{it}^{adj} = Y_{it} - X_{it}\hat{\beta}. \tag{2}$$

- log of real GDP/CAP (regional)
- asinh of daily COVID cases (regional)
- asinh commuting inflow (regional) ▸ scatter
- asinh working from home (regional)
- emission intensity of new vehicles (national)
- diesel and super prices in real terms (national)
- log of total freight goods loaded (regional)

▸ Projected

# Three specifications

1. No covariates.
2. Adjusted for COVID-19 related covariates.

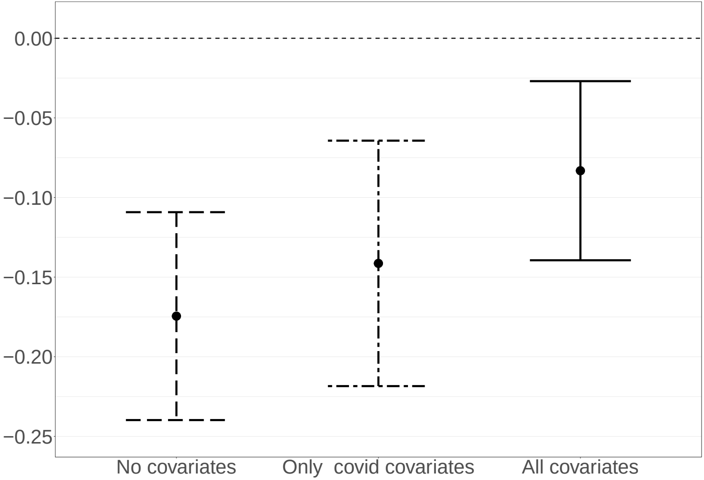
$$\begin{aligned} log(CO2/cap)_{it}^{co} =& \alpha_i + \gamma_t + \beta_1 asinh(cases)_{it}^{co} + \beta_2 asinh(comm)_{it}^{co} + \\ & \beta_3 asinh(wfh)_{it}^{co} + u_{it}, \end{aligned}$$

3. Full set of covariates (**main specification**)

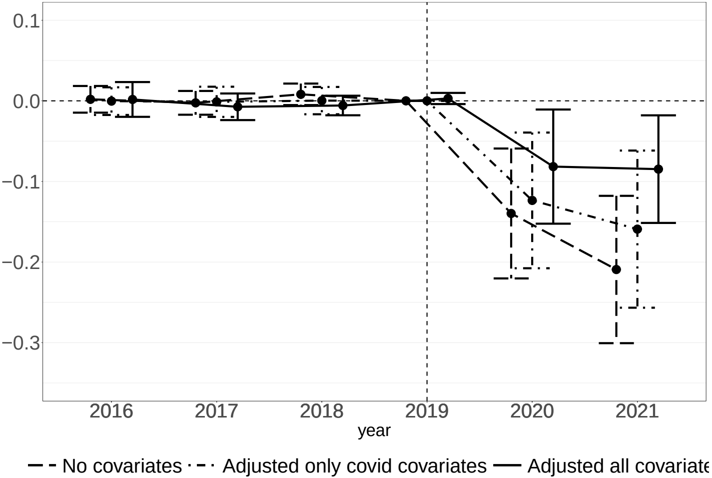
$$\begin{aligned} log(CO2/cap)_{it}^{co} =& \alpha_i + \gamma_t + \beta_1 asinh(cases)_{it}^{co} + \beta_2 asinh(comm)_{it}^{co} + \\ & \beta_3 asinh(wfh)_{it}^{co} + \beta_4 log(gdp)_{it}^{co} + \beta_5 ei_{it}^{co} + \\ & \beta_6 diesel_{it}^{co} + \beta_7 petrol_{it}^{co} + \beta_8 log(frt)_{it}^{co} + u_{it}. \end{aligned}$$

# Results - ATT

- ATT of −8% (specification with all covariates) ▸ Unit weights



# Results - Event Study



# Robustness

- Pre-trend with sdid weights ▸ pre-trend
- In-time placebo: 2018 treatment ▸ in-time placebo
- Different specificaions ▸ other specs
  - → exclude freight
  - → exclude wfh
  - → exclude commuting
- Leave one out ▸ leave one out
- Relative fuel prices (fuel tourism) ▸ rel fuel tab
- Energy for buildings ▸ energy for buildings
- Drop COVID years and extend to 2022 ▸ no COVID
- Administrative traffic counts monthly ▸ traffic counts

# Back of the envelope calculations

## 1. Effect size discussion

- Following figures from the European Commission and Directorate-General for Mobility and Transport (2021), let us assume a modal split for private vehicles and public transport of around 82% and 18%
- Assume emission reduction is due to a modal change from private vehicles to public transport
  $\longrightarrow$ Estimated increase of public transport: $(\hat{\tau}82\%/18\%) \approx 38\%$.
- In line with LuxMobile survey: 34% increase in public transport usage due to the free-fare policy

## 2. Marginal abatement cost of carbon

- Foregone revenue from ticket sales of around 41 Mio. Euros
- Compare to CO2 abated according to our estimates:
  $\frac{1}{T_{post}} \sum_{t=T_{pre}+1}^{T} CO2_t^{tr} / (1-\hat{\tau})$ $\longrightarrow$ EUR 114 per ton of carbon.

# Concluding Remarks

## Recap

- We study the *effect of free public transport on transport CO2 emissions*.
- We use SDID to create a comparable counterfactual to Luxembourg
- We control for potential confounders
  - → COVID, working from home, commuting, fuel prices, emission intensity of new vehicles, freight transport
- We estimate an *ATT of around* $-8\%$
- Results hold against robustness checks
- Framework to study other policies during Covid

## To-do

- Monthly data, other sectors, traffic volume counts, extended post-treatment period, drop Covid years, mechanisms, . . .

# Thank you

**Questions, comments, and suggestions are welcome**

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# References

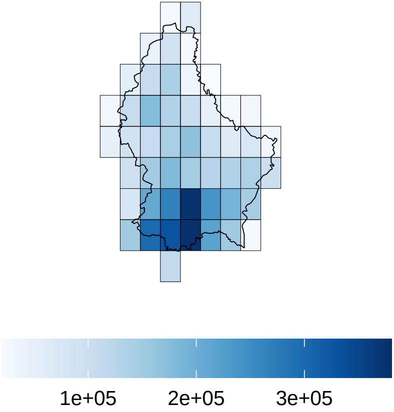

Arkhangelsky, D., Athey, S., Hirshberg, D. A., Imbens, G. W., & Wager, S. (2021). Synthetic difference-in-differences. *American Economic Review*, *111*(12), 4088–4118. https://doi.org/10.1257/aer.20190159

Clarke, D., Pailañir, D., Athey, S., & Imbens, G. (2023). Synthetic difference in differences estimation. https://arxiv.org/abs/2301.11859

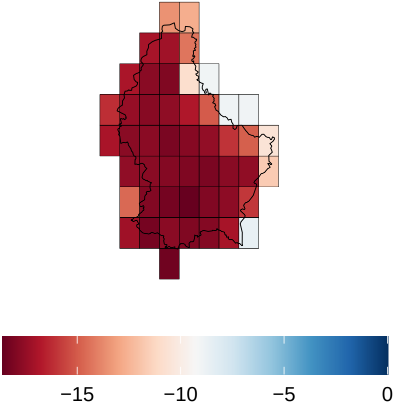
European Commission and Directorate-General for Mobility and Transport. (2021). *Eu transport in figures – statistical pocketbook 2021*. Publications Office. https://doi.org/doi/10.2832/27610

Kranz, S. (2022). *Synthetic difference-in-differences with time- varying covariates. technical report*. https://github.com/skranz/xsynthdid/blob/main/paper/synthdid%20with%20covariates.pdf

# Evolution of road transport emissions from LU




((a)) Average Emissions 2016–2019




((b)) %-Change 2020–2021 vs. 2016–2019

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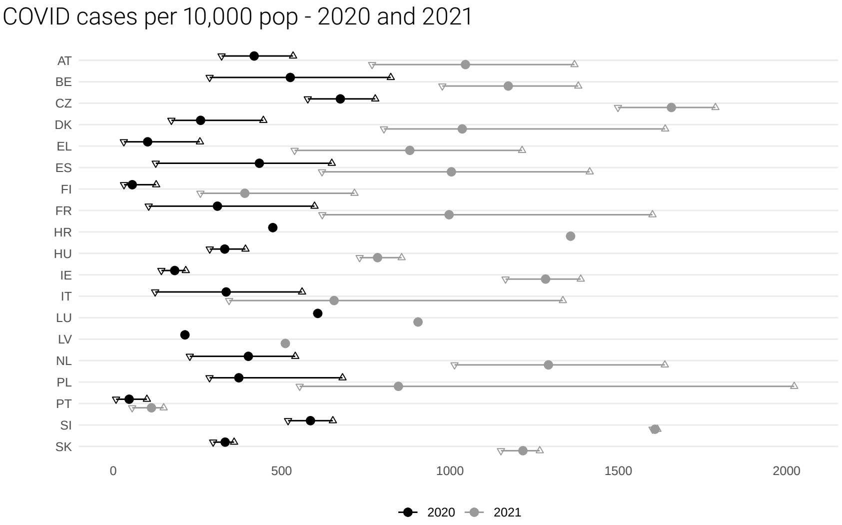
# COVID - 19

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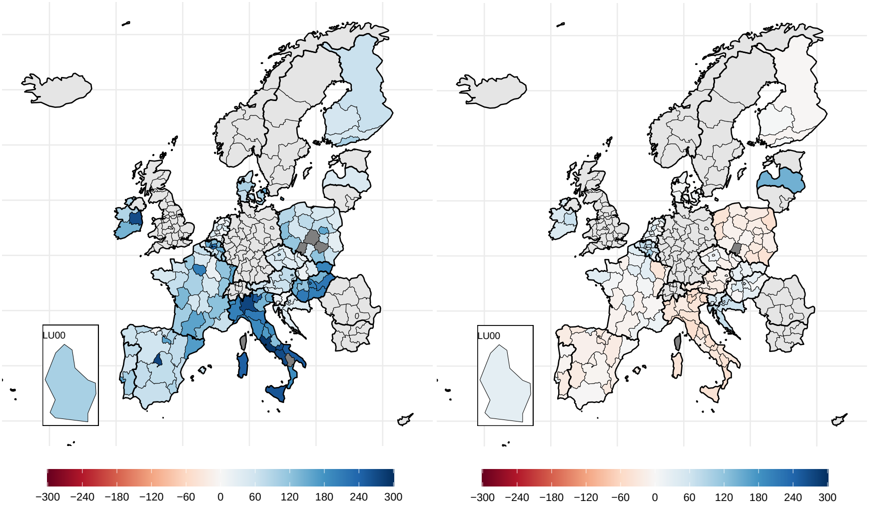
# COVID - 19 cont ...

Change (%) usually wfh in country of residency: 2019-2020 and 2020-2021

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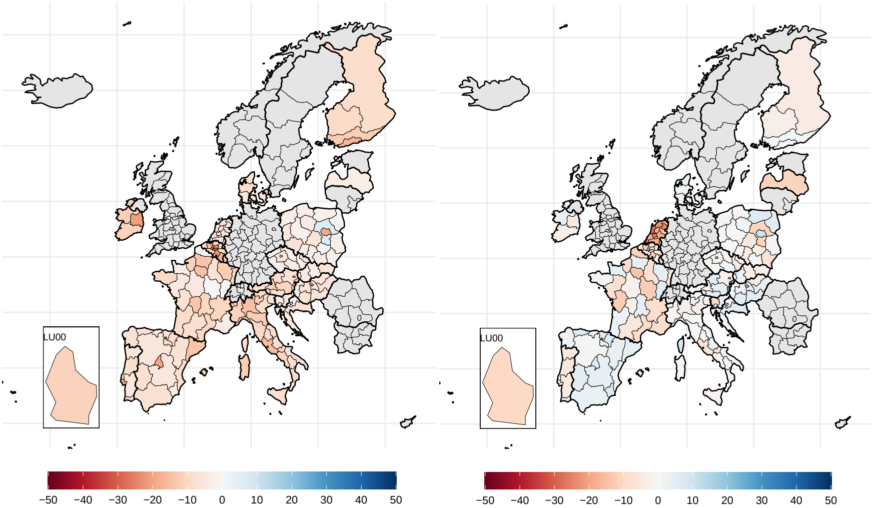
# COVID - 19 cont...

Change (%) commuting inflow irrespective of residency: 2019-2020 and 2020-2021

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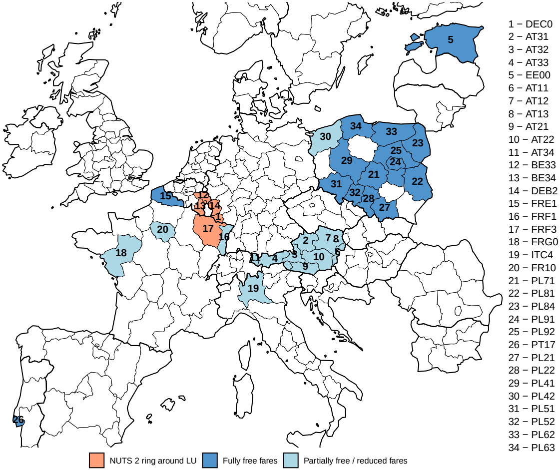
# Bad comparisons and spillovers (2016-2021)

- Exclude NUTS 2 ring around LU
- Exclude regions that introduced fully free fares during sample period (2016-2021)

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**Synthetic DiD**

$$\left(\widehat{\tau}^{sdid}, \widehat{\mu}, \widehat{\alpha}, \widehat{\beta}\right) = \underset{\tau,\mu,\alpha,\beta}{\arg\min} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\tau)^2 \widehat{\omega}_i^{sdid} \widehat{\lambda}_t^{sdid} \right\}$$

**Synthetic Control**

$$\left(\widehat{\tau}^{sc}, \widehat{\mu}, \widehat{\beta}\right) = \underset{\tau,\mu,\beta}{\arg\min} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \beta_t - W_{it}\tau)^2 \widehat{\omega}_i^{sc} \right\}$$

**DiD**

$$\left(\widehat{\tau}^{did}, \widehat{\mu}, \widehat{\alpha}, \widehat{\beta}\right) = \underset{\tau,\mu,\alpha,\beta}{\arg\min} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\tau)^2 \right\}$$

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**Unit weights** are computed to align pre-treatments trends between treated and control units:

$$\left(\widehat{\omega}_0, \widehat{\omega}^{sdid}\right) = \underset{\omega_0 \in \mathbb{R}, \omega \in \Omega}{\arg\min} \sum_{t=1}^{T_{pre}} \left( \omega_0 + \sum_{i=1}^{N_{co}} \omega_i Y_{it} - \frac{1}{N_{tr}} \sum_{i=N_{co}+1}^{N} Y_{it} \right)^2 + \zeta^2 T_{pre} ||\omega||_2^2.$$

**Time weights** are computed to align pre- and post-treatment periods of control units:

$$\left(\widehat{\lambda}_0, \widehat{\lambda}^{sdid}\right) = \underset{\lambda_0 \in \mathbb{R}, \lambda \in \Lambda}{\arg\min} \sum_{i=1}^{N_{co}} \left( \lambda_0 + \sum_{t=1}^{T_{pre}} \lambda_t Y_{it} - \frac{1}{T_{post}} \sum_{t=T_{pre}+1}^{T} Y_{it} \right)^2 + \zeta^2 N_{co} ||\lambda||^2.$$

- $N_{co}$ and $N_{tr}$ are the number of untreated and treated units.
- $T_{pre}$ and $T_{post}$ are the number of pre- and post-treatment periods.
- $\zeta$ is a regularization parameter to increase dispersion and ensure unique weights as defined in Arkhangelsky et al. (2021)

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## Covariates - Projected

| | (1) | | (2) | |
|---|---|---|---|---|
| | Coef. | SE | Coef. | SE |
| asinh(cases) | −0.0300*** | (0.0032) | −0.0181*** | (0.0060) |
| asinh(comm) | 0.0412 | (0.0303) | 0.1881*** | (0.0553) |
| asinh(wfh) | −0.0446*** | (0.0071) | −0.0443*** | (0.0106) |
| log(gdp) | 0.2649*** | (0.0776) | | |
| ei | 0.0036*** | (0.0004) | | |
| diesel | −0.6570*** | (0.0747) | | |
| petrol | 0.0631 | (0.1274) | | |
| log(frt) | 0.0001 | (0.0081) | | |
| Obs | 822 | | 822 | |
| N | 137 | | 137 | |

Notes: Dependent variable is $lco2cap$, standard errors are clustered at the regional level.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$

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## Placebo Inference

Confidence bands around the estimated $d_t$'s are generated with a placebo-based approach in the following sequence:

1. Exclude the treated unit (in our case Luxembourg) from the sample
2. Randomly assign treatment to a unit (from the remaining units, which are all controls units)
3. Calculate the outcome adjusted for covariates, i.e., $\hat{Y}_{it}^{adj}$.
4. Compute $d_t$ and store the result
5. Repeat 2-4 many times (e.g., 1,000 times)
6. Obtain the 5% quantile from the sample distribution of the stored results for each time period $t$.

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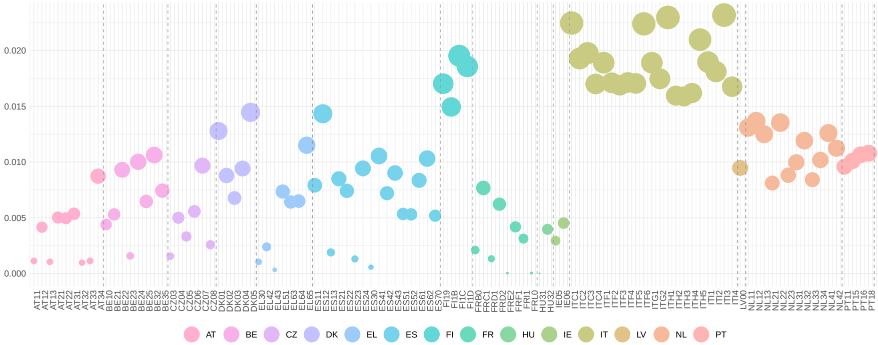
# Unit weights - all covariates

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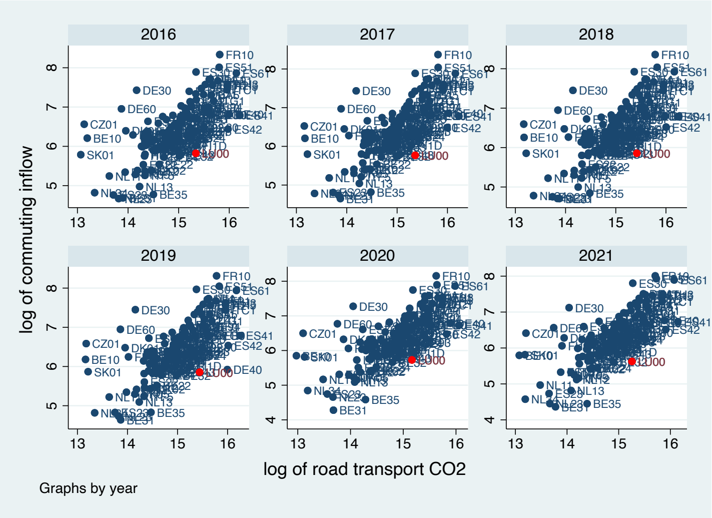
# Commuting inflow scatter plot

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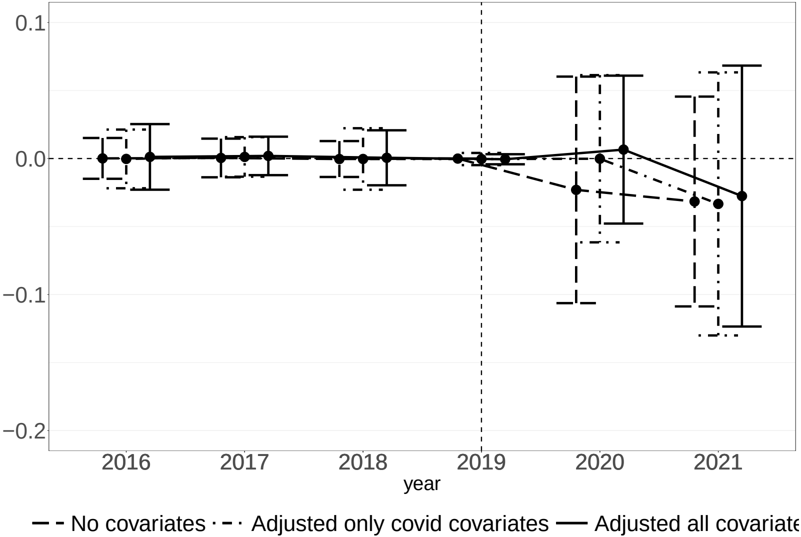
# Energy use in the building sector

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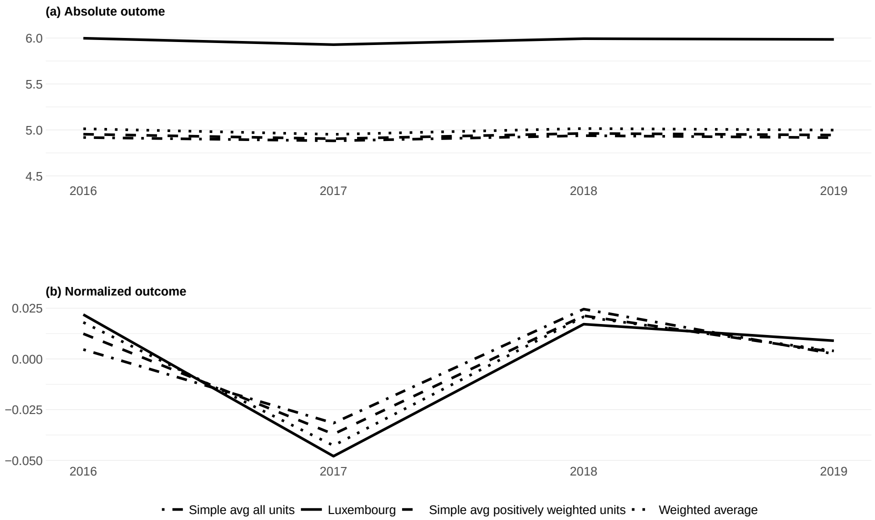
# Trend comparisons - normalized

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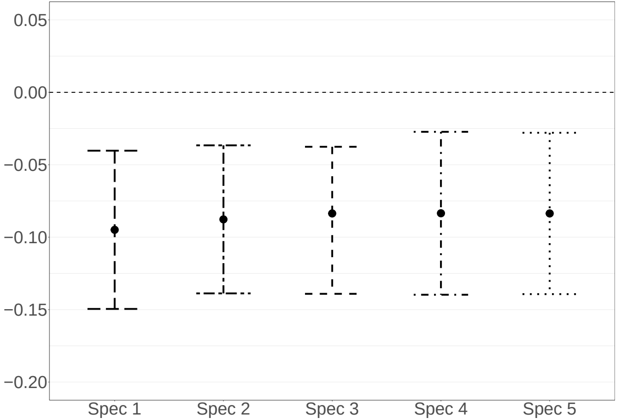
# Robustness tests - ATTs across different specifications




Notes: *Spec 1* excludes controls for freight transport; *Spec 2* excludes controls for working from home; *Spec 3* excludes controls for both freight and working from home, *Spec 4* excludes controls for commuting (never working from home); *Spec 5* excludes controls for both freight and commuting

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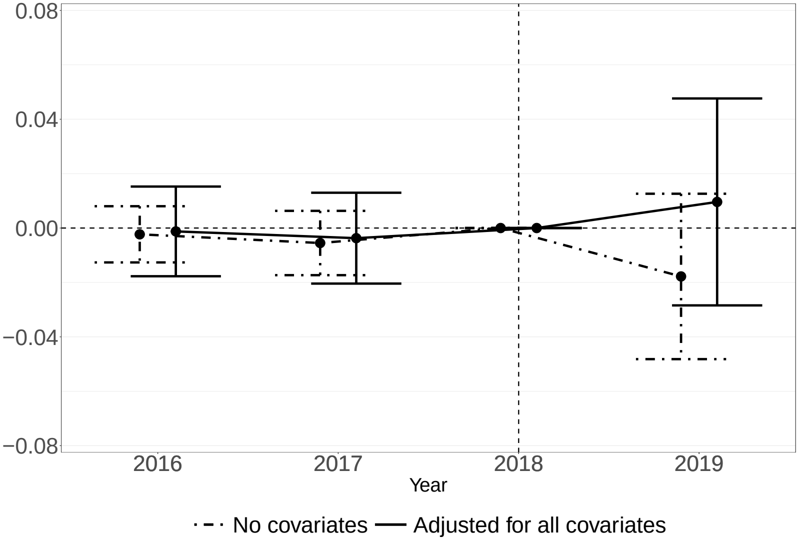
# In-time placebo

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# Drop COVID years and extend to 2022

Drop COVID years (20/21) and extend to 2022. Several things apply:

- LUX improved public transport in 2022, we cannot extract this effect
- 2022 emission data are preliminary and subject to change
- LUX's fuel prices relative to neighbors increased strongly

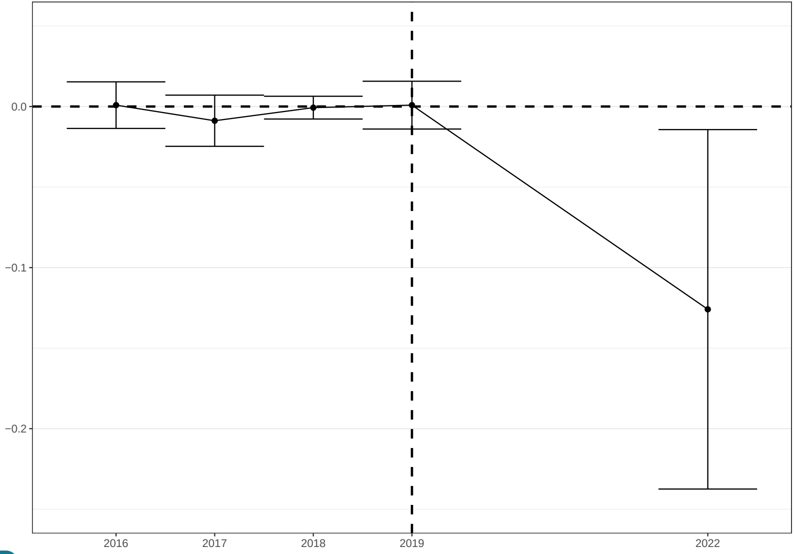
We adjust the outcome for **cross-border commuting inflow fully interacted with rel. fuel prices** (weighted avg) to neighbors.

Cross-border commuting in four distinct categories based on distribution.

We drop COVID-related covariates (cases, wfh, overall commuting)

ATT: $-12\%$ $\longrightarrow$ Implies a drop of 3.7pp in 2022 rel. to 2021. es

# Drop COVID years and extend to 2022

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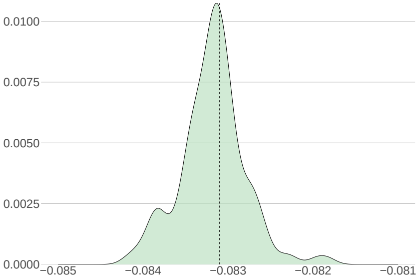
# Leave one out




((a)) Dropping a region from the donor pool

((b)) Dropping a country from the donor pool

Figure: Distribution of ATT: leave one out analysis

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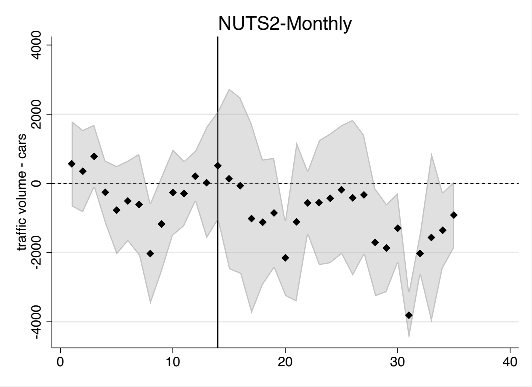
# Traffic Counts (Super Preliminary)

- SDiD on monthly average of traffic counts in Nuts2 regions of LU against FI and DK
- jan2019-dec2023, excluding Covid (mar2020-dec2021).
- ATT: $\sim -10\%$

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# Relative fuel prices

Table: Pre- and post-treatment averages of relative fuel prices for Luxembourg

| | Diesel | | Petrol | |
|---|---|---|---|---|
| | Pre-Avg | Post-Avg | Pre-Avg | Post-Avg |
| BE | 0.7825 | 0.8028 | 0.8869 | 0.8814 |
| DE | 0.8684 | 0.8759 | 0.8493 | 0.8368 |
| FR | 0.7585 | 0.8056 | 0.8001 | 0.8182 |

Note: Relative fuel prices of LU with respect to its neighboring countries. Pre-Avg are relative fuel prices based on time-weighted pre-treatment fuel prices, where time weights are taken from the SDiD main specification. Post-Avg are relative fuel prices based on post-treatment fuel prices.

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