The effect of Low Emission Zones in the Economy: A Synthetic Control approach to German cities

Antonio Avila - A.Avila2@lse.ac.uk

LSE

July 19, 2020

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Who am I?

Pollution and Low Emission Zones

- 92% of the world's population lives in areas where levels of air pollution exceed the WHO guidelines
- 3 million deaths a year being attributed to air pollution. (Shaddick et al., 2018)
- Strong European legislation has been passed on the topic.

LEZ in the EU and Germany

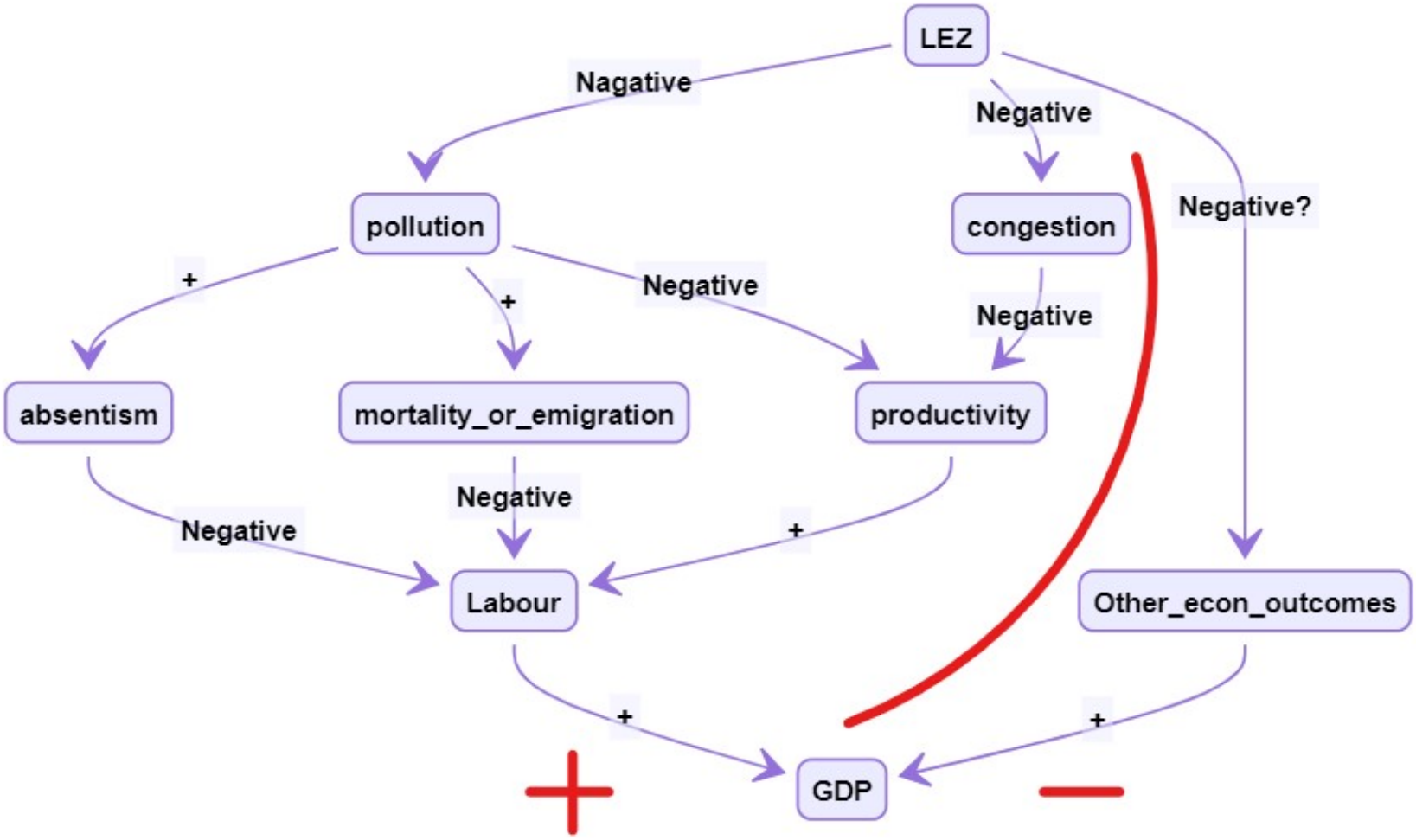
- More than 60% of German cities with more than 100.000 persons were transpassing European pollution limits (from 2005 to 2007) and **were forced** to develop "Clean Action Plans", almost all of them including a LEZ (Gehrsitz, 2017).
- German LEZ are supported and standardised by the federal government. They apply the same restrictions, stages and fines.
- Hundreds of LEZ have been applied in Europe, with Germany and Italy having the largest numbers

Theoretical background

- We would expect these policies to damage a city's economy as they involve taxes and prohibitions for certain vehicles.
- Reducing congestion and pollution might offset other economic costs.

This hypothesis is based on...

New evidence on the effect of pollution in the economy:



Reference literature of the diagram

- LEZ $\Downarrow$ Pollution: Wolff (2014), Gehrsitz (2017),
- LEZ $\Uparrow$ Mobility: Kelly and Kelly (2009),
- LEZ $\Downarrow$ Health costs: Cesaroni et al. (2012) and $\Uparrow$ moratlity: Xie et al. (2016)
- Pollution $\Downarrow$ GDP: Dechezleprêtre (2018); Hao et al. (2018),
- Pollution $\Downarrow$ Productivity: Adhvaryu et al. (2014); Chang et al. (2016); Graff-Zivin and Neidell (2012),
- Pollution $\Uparrow$ Absentism: Hanna and Oliva (2015); Ransom and Pope (1992) and Laura Hospido,
- Pollution $\Downarrow$ Cognitive performance: Ebenstein et al. (2016); Roth (2015); Zhang et al. (2018)

Why **German** LEZ?

- Availability of previous research on significant reduction of pollution (Gehrsitz, 2017; Wolff, 2014)
- Exogenous incentive from European legislation
- Standardisation of LEZ by the federal government
- Availability of detailed data on implementation

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Research Questions:

Main question:

- The effect of LEZ on German cities' economies

Complementary questions: *(subject to time constraints)*

- Which economic sectors are more affected by the policy?
- What would be the effect of a LEZ in other German or European cities that have not applied it?*

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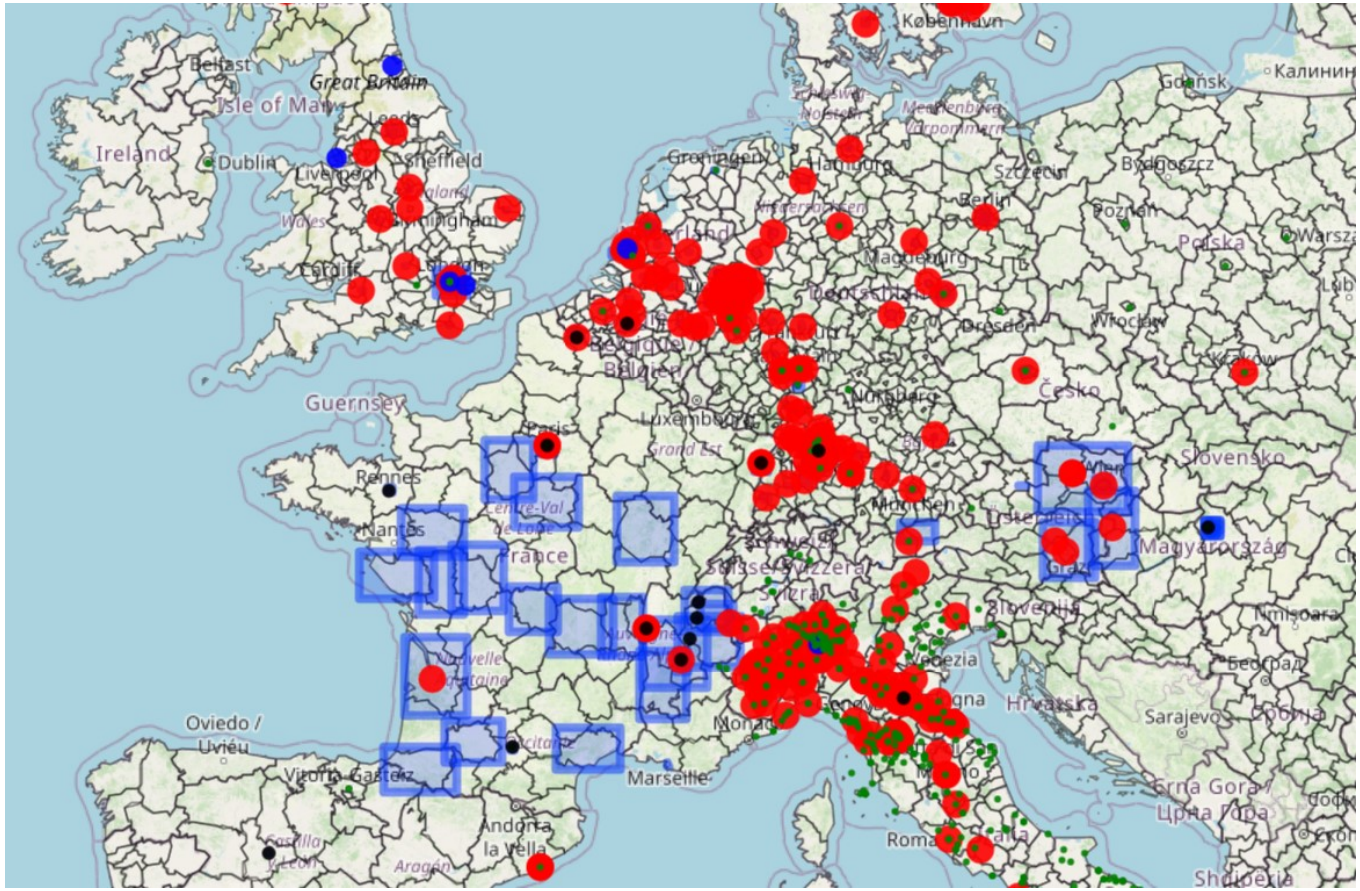
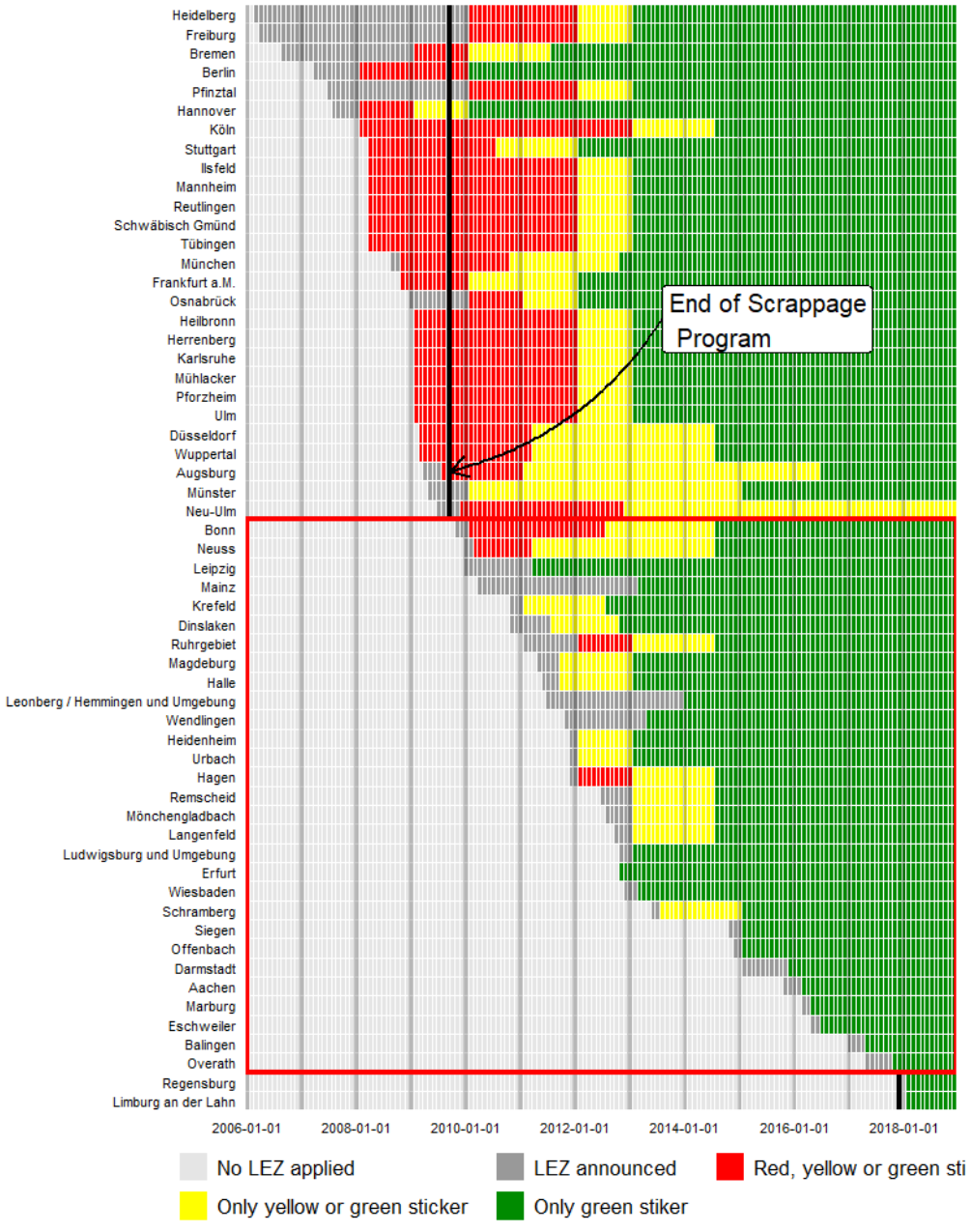
Data collection

- Economic and demographic variables → *Eurostat*, *NUTS regions*
- Application of LEZ zones and similar policies:
  - Germany → *Umweltbundesamt* and official documents of LEZ announcements.
  - Rest of Europe → *UAR* and *"Green Zones"* App.

Treatment status in Europe



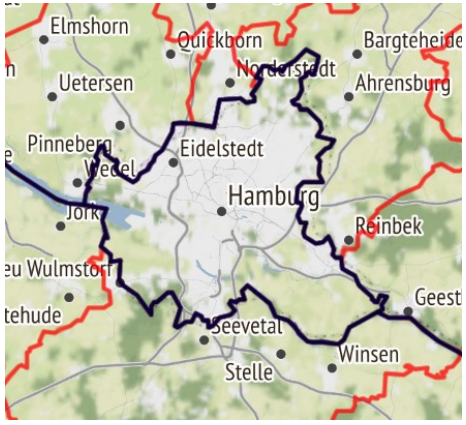
Temporal application of LEZ in Germany and EU



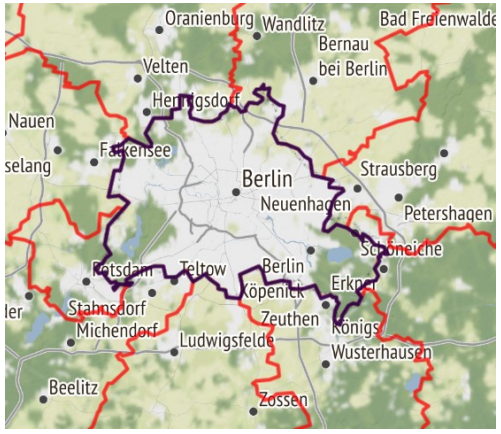
Units of study - NUTS regions

Figure 1: Main coverage of NUTS zones across Europe and Germany

Units of study - Cities from NUTS 3 regions

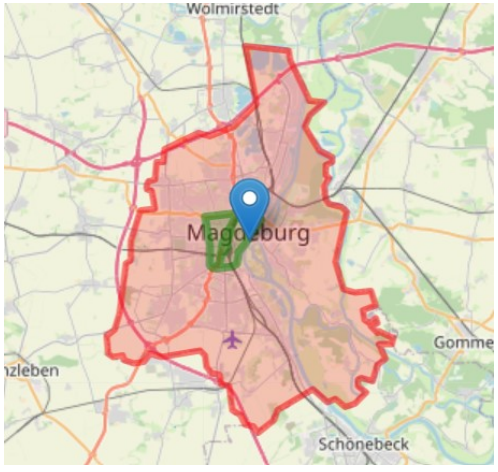


(a) Hamburg

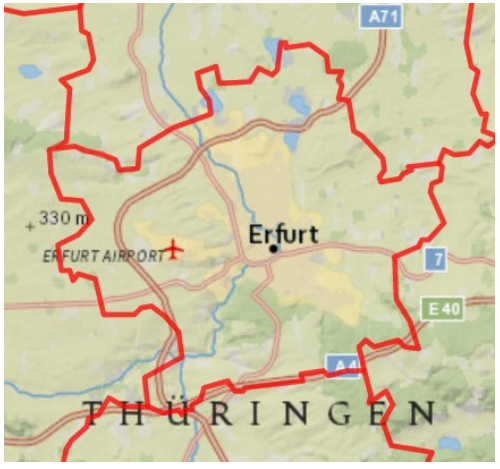


(b) Berlin

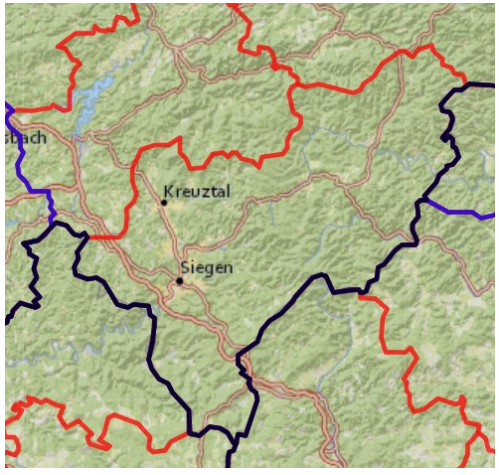
(c) Munich



(d) Magdeburg



(e) Erfurt



(f) Siegen (small)

Figure 2: Cities and their NUTS regions

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What are we going to **do**?

a) Estimate with a Synthetic Control the effect of LEZ for

1. Overall GDP/capita (main effect)
2. Relative GVA for relevant sectors. (Still not finished)
   - GVA Retail / Total GVA
   - GVA Transport / Total GVA
   - GVA Public sector / Total GVA

b) Use the idea of a new "Synthetic Treated Method" to estimate the potential effect of a LEZ in non-treated cities.

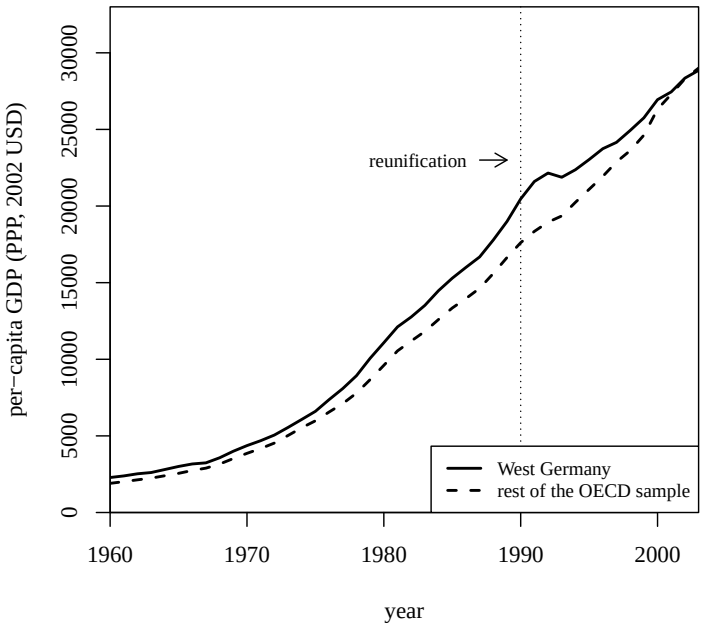
Introduction on the Synthetic Control Method (SCM) (1)

The SCM works very similar to Difference-in-Differences (DID), both

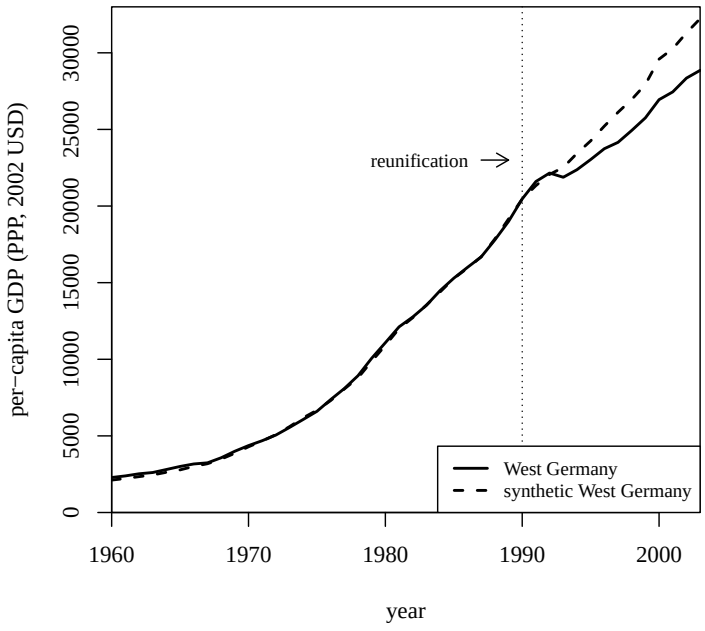
- Their main identification requirement is having a comparable control with similar trends before treatment
- Do not assume an exogenous treatment assignment

The difference is how the counterfactual unit is chosen, while DID is mostly theory-based **the SCM can be though as a data-based procedure to find the best DID counterfactual possible from a weighted average of control regions**.

Introduction on the SCM (2)



(a) West Germany and the mean of the control pool



(b) West Germany and its synthetic control

Figure 3: We can see how the Synthetic control closely follows the pre-intervention path of West Germany and deviates from if after the intervention.

Source: Abadie et al. (2015).

SCM (3) - Linear Factor Models and **Gsynth**

Gsynth doesn't estimate weights from control units but characterizes the treated region as a set of comon factors and factor loadings that predict its counterfactual path.

$$y_{it} = y_{it}^{(0)} + \tau_{it} d_{it}$$
$$y_{it}^{(0)} = \boldsymbol{x}_{it}^{\top} \boldsymbol{\theta} + \boldsymbol{\lambda}_i^{\top} \boldsymbol{f}_t + \varepsilon_{it}$$

Where $y_{it}^{(0)}$ is the counterfactual, τ_{it} is the treatment effect and d_{it} is a treatment dummy
$\boldsymbol{f}_t = (f_{1t}, ..., f_{Jt})$ are J time-varying factors ("shocks"), and
$\boldsymbol{\lambda}_i = (\lambda_{i1}, ..., \lambda_{iJ})$ are unit-specific factor loadings ("responses").

Generalised Synthetic control method

Xu (2017) proposes a three-step estimation procedure:

1. Control units are used to estimate θ, $f1, ..., f_T$ and $\lambda_1, ..., \lambda_{n1}$ minimising $(y_{it} - \hat{y}_{it}^{(0)})^2$
2. Obtain estimated factor loadings for the treated units, $\hat{\lambda}_i (i > n1)$ conditional of the first step by minimising the MSE between y_{it} and $\hat{y}^{(0)}$ in the pre-intervention period
3. Estimate the intervention effects as $y_{it} - y_{it}^{(0)}$ in the post-treatment period for the treated units.

Generalised Synthetic control method (2)

- Allows for positive and negative "implied" weights *as Doudchenko and Imbens (2016)*
- N° of factors chosen by cross-validation to minimise out-of-sample MSE
- Standard errors calculated by a bootstrap procedure
- R package includes the use of lags to improve accuracy from Gobillon and Magnac (2016)

A good summary of these methods and other similar ones can be found in Samartsidis et al. (2019).

Identifying assumptions

So what do we need?

- **Non interference between units/cities:** A LEZ seems to create changes in fleet composition of the surrounding area so the controls are restricted to +60km of any LEZ.
- **Valid comparison group:** Large European pool of controls
- **Sizeable effect:** Effect of the policy should be bigger than individual shocks or data noise.
- **No anticipation:** Use date of announcement instead of implementation.
- **Sufficient pre-intervention data:** 9-16 years
- No significant contemporaneous local policies/events

Robustness tests

- Quality of the synthetic control
- Significance of the estimates (Boostrap procedure in **Gsynth**)

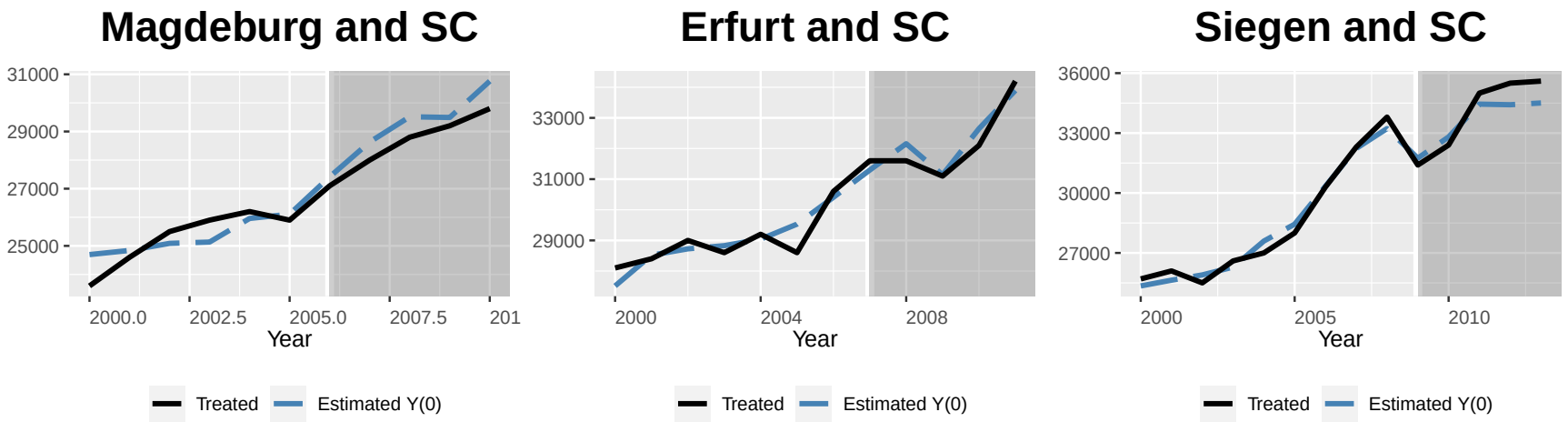


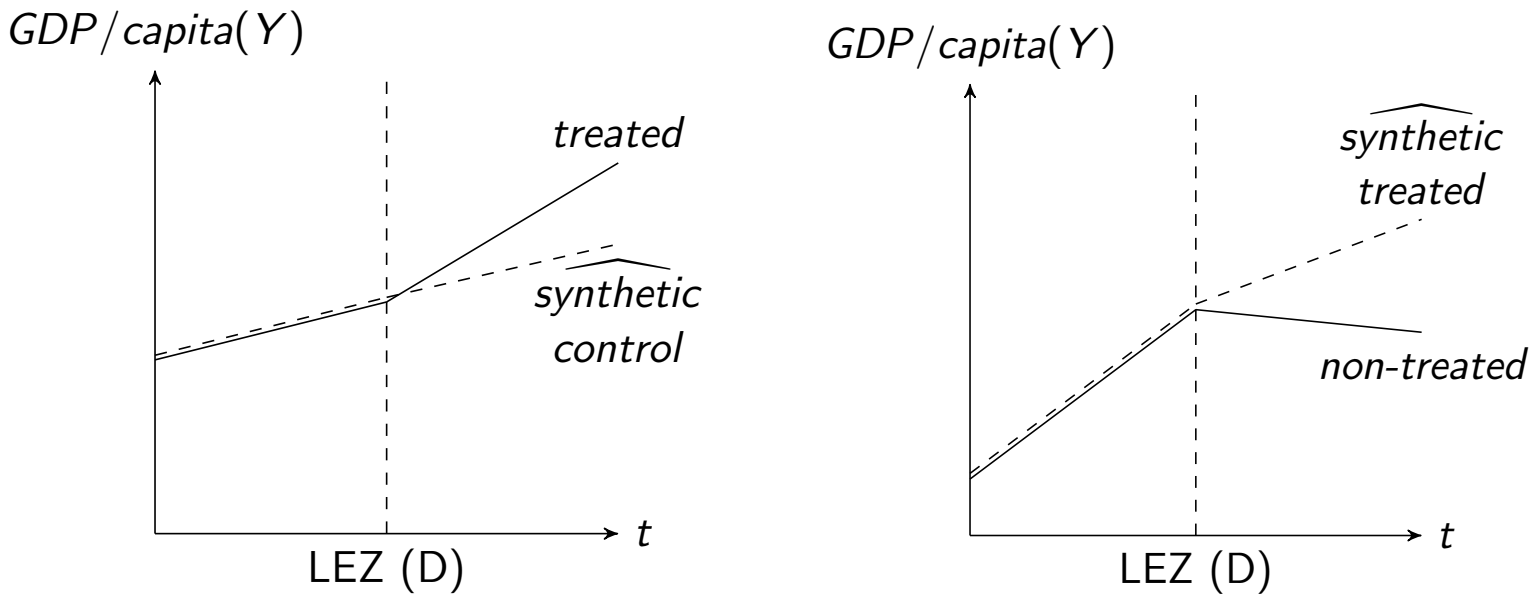
Figure 4: Examples of pre-intervention placebos (4 years)

Synthetic Treated Method

The idea:

The same method that creates and and validates a *synthetic control* (counterfactual) for a given treated unit, can create a *"synthetic treated"* and evaluate the potential treatment effect in a non-treated unit.

The potential treatment effect on non-treated regions



(a) Classic SCM

(b) "Synthetic Treated Method"

Figure 5: Same main idea, properties, proofs, and robustness tests. We only change the pool of controls for a pool of treated regions and estimate the potential treatment effect on non-treated.

Notes on creating counterfactuals for **control** regions

- Not restricted to Synthetic controls but works with all methods that are based on creating a counterfactual from units that have a different treatment status (DID, Latent factor models, Synthetic controls, ...)
- As DID, SCM and LFM it is important **who** you are comparing with.
- Not the best setting for a demonstration
  1. Too few treatment observations per year to create a large "treated pool"
  2. Unclear "treatment": varying relative size of LEZ and different implementation calendars

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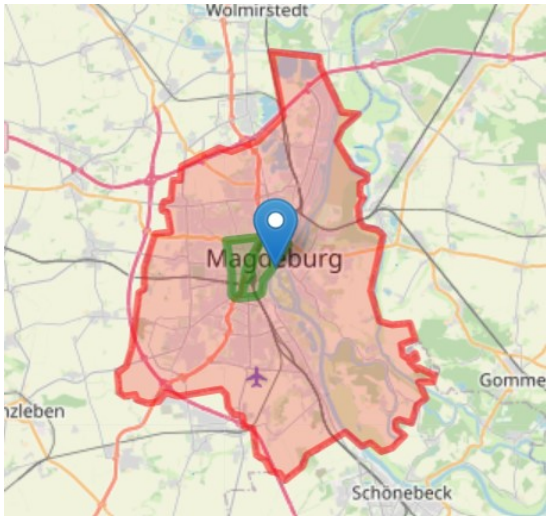
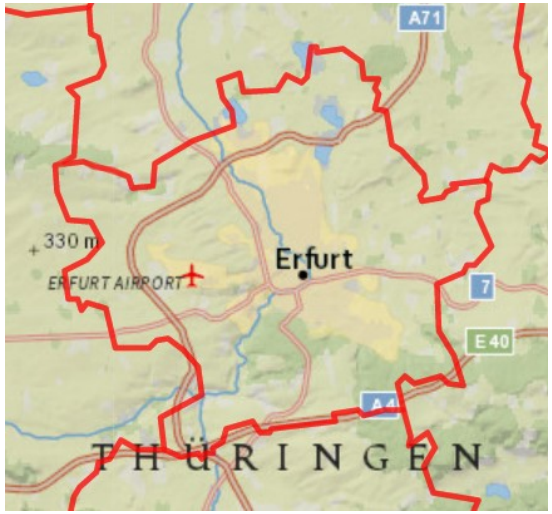
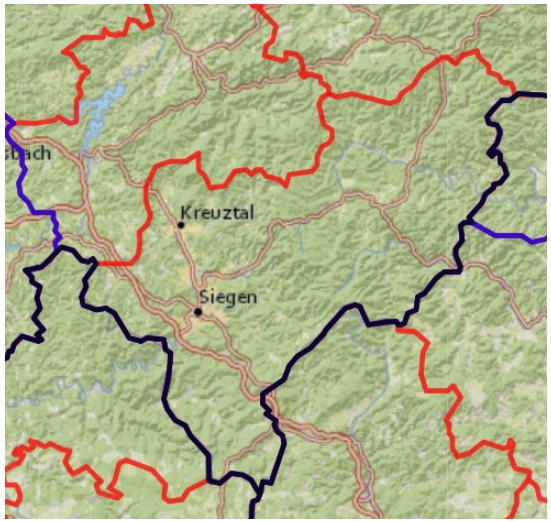
The effect on GDP/capita - Presentation of cases



(c) Magdeburg



(d) Erfurt



(e) Siegen (small)

Figure 6: Examples of 3 treated cities and their NUTS3 regions

The effect on GDP/capita - Individual results

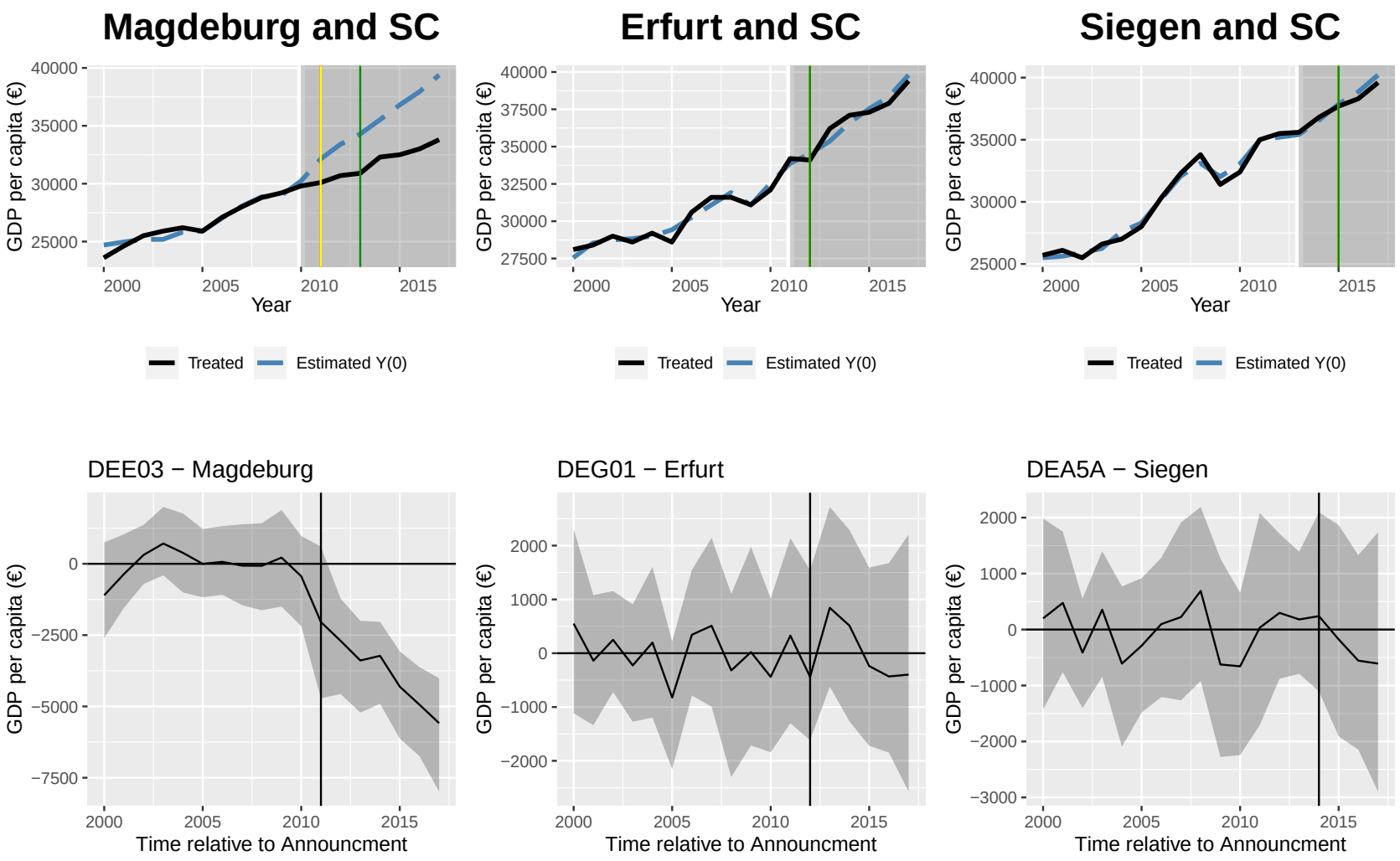
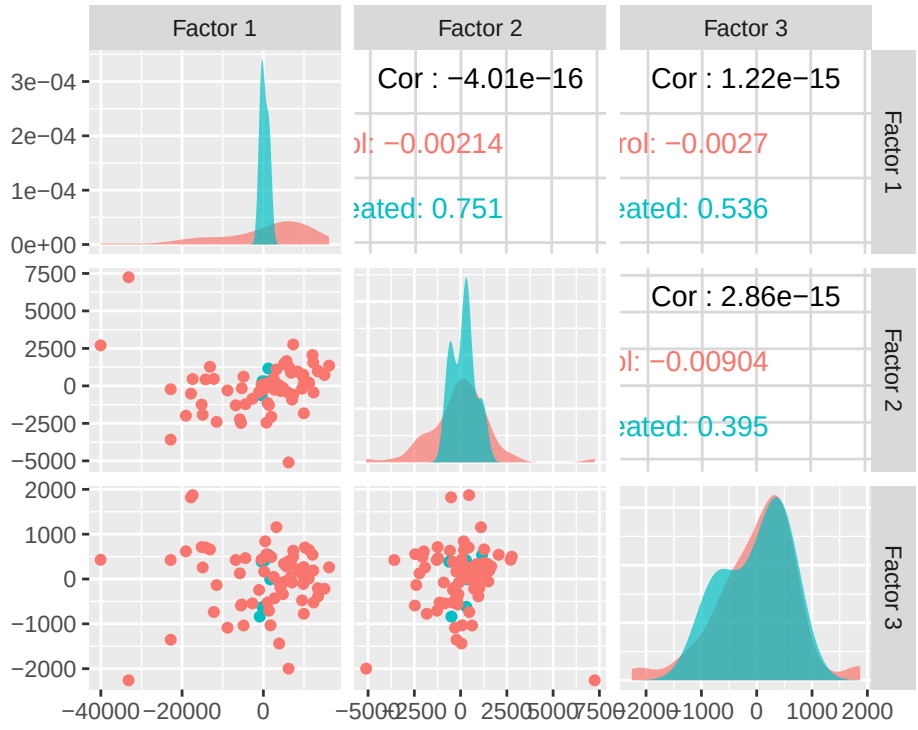
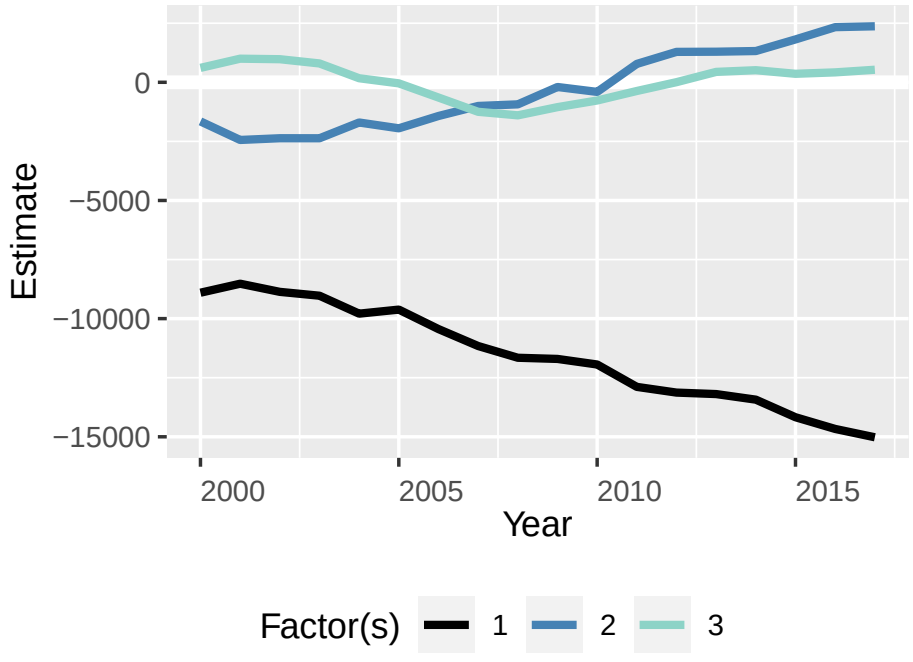


Figure 7: Results

The effect on GDP/capita - Diagnostics



(a) Factor Loadings



(b) Factor Evolution

Figure 8: Time-varying factors control for important heterogeneity and estimations are done within the support of the data.

The effect on GDP/capita - Factor interpretation

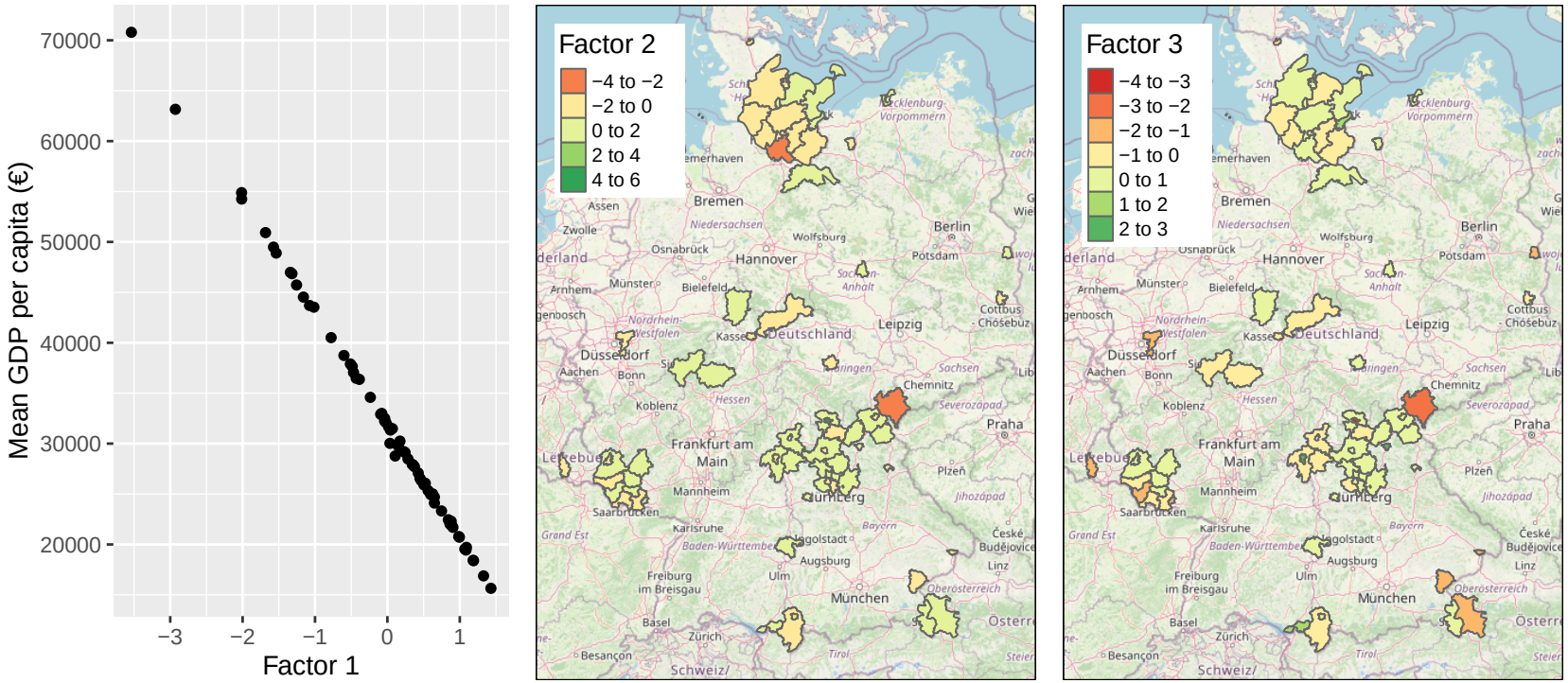


Figure 9: Factors interpretation and spatial distribution.

The potential treatment effect on non-treated regions

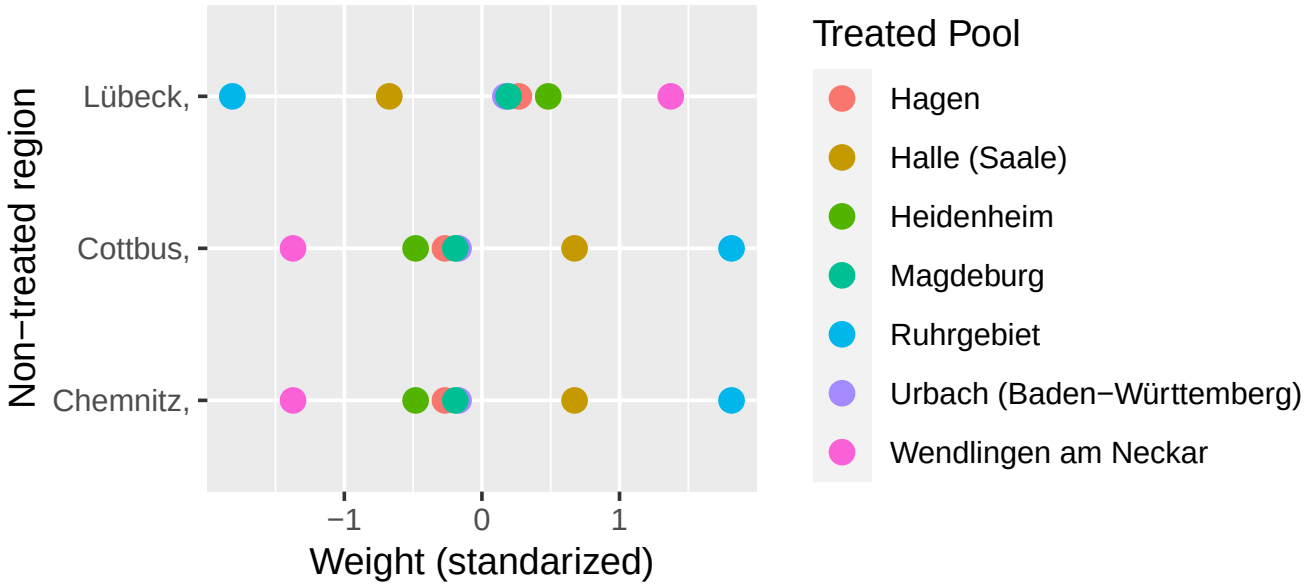
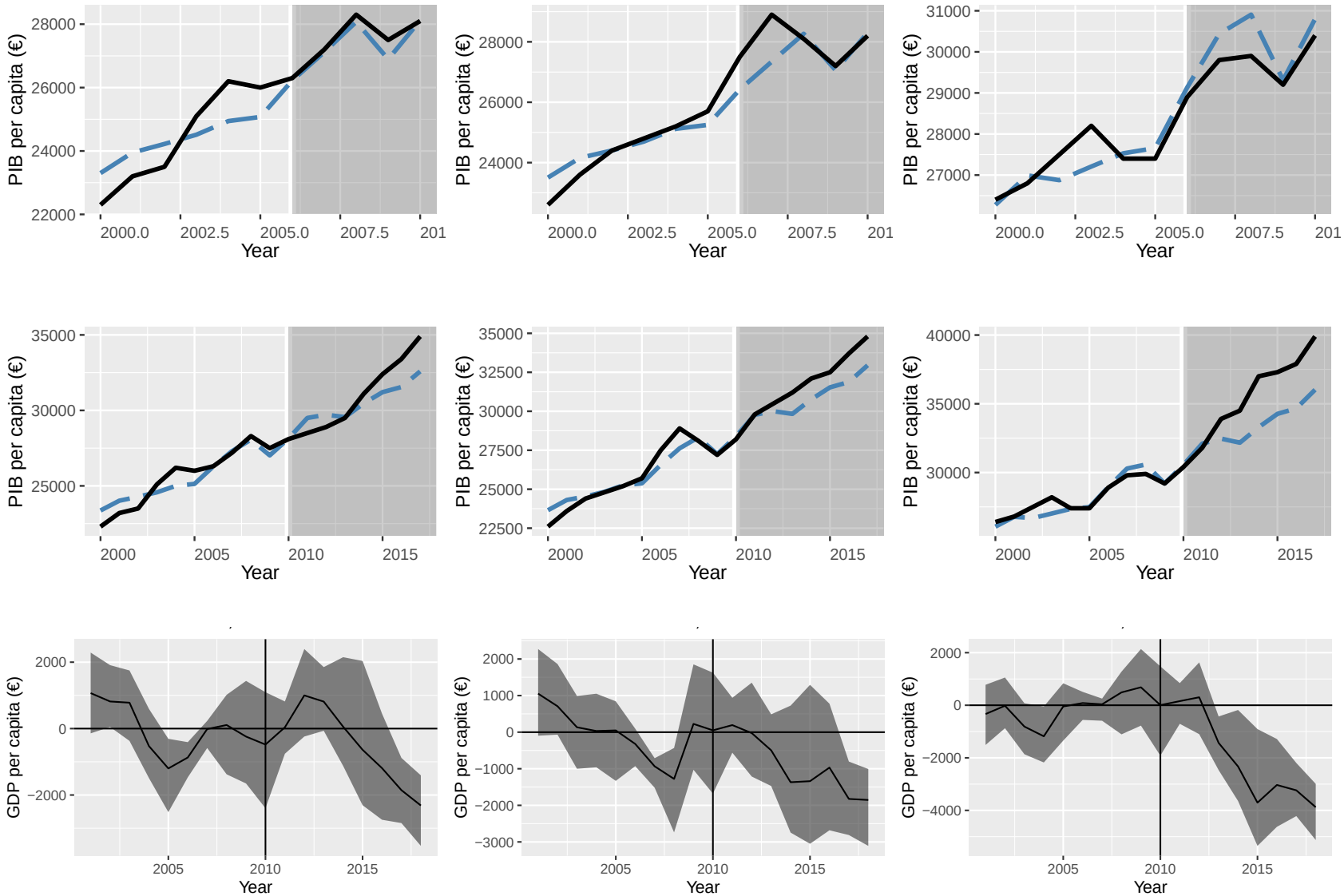


Figure 10: Implied weights of each non-treated region for each treated in 2011.

It can be from any year but this restricts the "treated pool" and thus changes the estimate if the effect varied between cities.

Results of the Synthetic Treated Method



(g) Cottbus (h) Chemnitz (i) Lübeck

Figure 11: Results of potential treatment effects for non-treated cities in 2010

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Next steps and discussion

Next steps:

- Contact localities (such as Magdeburg) to check for any strong economic shock in the post-intervention period.
- See the effect on each sector, especially retail and transport.

Points I would like to discuss:

- Credibility of the main results
- How you perceived the "Synthetic Treated" idea, possible weak points and related literature.
- Anything else!

Thanks!

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