Research Design for a Scientific Paper

of 41783 - Seminar 5

London School of Economics

The effect of Low Emission Zones in economic outputs: A synthetic control approach to German cities.

Abstract

Air pollution is a growing public concern due to its effects on health and mortality, and numerous policy initiatives have been applied to reduce it. In Europe, and especially in German cities, Low Emission Zones (LEZ) have been widely adopted and proven successful in reducing air pollution. While these policies are criticised for "hurting the economy", recent literature indicates how air pollution negatively affects inputs of production, especially labour, making LEZs a policy that can both harm and boost economic growth. To solve this contradiction from a program evaluation perspective, I propose the use of a Synthetic Control Method (SCM) to study the effect of German LEZ in their local economy and labour outcomes and the Mediation Analysis Synthetic Control (MASC) to investigate how pollution mediates this causal effect. This research can provide a concrete answer to a pressing question for local authorities, academics and the broad public by providing city-specific estimates by economic sector accounting for the heterogeneity of implementation formulas and the mediator effect of pollution.

Keywords — Synthetic Control, Low Emission Zones, Air Pollution, Germany, GDP, Labour effects, Economic Geography

Word count: 3990

1 Literature review

Recent research estimates that 92% of the world's population lives in areas where levels of air pollution exceed the World Health Organization's guidelines, with 3 million deaths a year being attributed to air pollution (Shaddick et al., 2018). In order to minimise these costs, substantial policy initiatives aimed at improving air quality have been implemented around the world. Cities and urban areas play a central role in this effort as virtually half of the world's total population - around 3 billion people - now live in urban settlements, a number that has greatly increased during the last 20 years (Cohen, 2006). With higher population density both traffic congestion and air pollution have also risen, resulting in increasing health and economic costs.

In European cities, Low Emission Zones (LEZ) have proven popular when trying to improve air quality and comply with the increasingly strict EU regulations (Holman et al., 2015). Germany has been in the forefront of the application of LEZ with most German cities over 10.000 inhabitants having applied one from 2008 to 2013 (Gehrsitz, 2017). German LEZ have been supported and standardised by the federal government. All of them apply the same restrictions to high-polluting cars and are implemented in the same stages. Entering a LEZ without authorisation is fined with 80€ and implies a 1 demerit point in the central traffic registry (Gehrsitz, 2017).

According to classic economic theory, we would expect these policies to damage a city's economy as they involve taxes and prohibitions for certain vehicles, leading to claims of a "Jobs versus the Environment" trade-off as introduced by Morgenstern et al. (2002). The impact of LEZ on economic outputs such as economic growth, profits and employment has been a constant concern of citizens and local officials. And their concern is not unjustified. Most large cities that constitute the backbone of the German economy have applied restrictive LEZ (Berlin, Munich, Köln, Hannover, Dortmund and Stuttgart are some examples). It is crucial to know how Germany's economy has been affected by these predominant environmental measures to be able to develop a fair cost-benefit analysis of them.

However, the effects of reducing congestion and pollution might offset other economic costs. This hypothesis is based on recent research on the effect of LEZ on increasing mobility (Kelly and Kelly, 2009) and decreasing health costs (Cesaroni et al., 2012) and air pollution by Wolff (2014) and Gehrsitz (2017) (who give results for German LEZ). Furthermore, recent studies suggest that air pollution reduces aggregate economic output (Dechezleprêtre, 2018; Hao et al., 2018). This can happen through various labour-market effects such as increasing mortality (Xie et al., 2016), reducing productivity (Adhvaryu et al., 2014; Chang et al., 2016; Graff-Zivin and Neidell, 2012) and cognitive performance (Ebenstein et al., 2016; Roth, 2015; Zhang et al., 2018) or increasing absenteeism (Hanna and Oliva, 2015; Ransom and Pope, 1992).

There is also strong evidence that a very significant proportion of cities' air pollution comes from traffic, with 35-55% of PM_{10} particles coming from vehicles in EU cities (Viana et al., 2008). For Berlin, traffic produces a 38% and 23% of pollution gathered in close-to-traffic and background stations, respectively (Lenschow et al., 2001). Finally, there is strong causal evidence that the application of German LEZ has significantly reduced particle pollution inside them between 2 and 9% (Gehrsitz, 2017; Wolff, 2014).

In the European Union, most regional and national governments have been either threatened by fines or strongly incentivised to pursue decisive policy action by European regulation. From 2005 to 2007 two thirds of German cities with more than 100.000 persons were violating European limits and were forced to develop "Clean Action Plans", most of them including a LEZ (Gehrsitz, 2017). As a result of this legislation, the European Commission (EC) has opened infringement procedures against 16 Member States and the EU Court of Justice has already handed down judgements in Bulgaria and Poland[1].

For the availability of previous research, the standardisation of LEZ by the federal government, the exogenous incentive from European legislation and the availability of data (discussed in the "Data collection strategy" section), I am confident that German LEZ are the best subject of study to understand the causal effects between a strong environmental policy such as LEZ and economic performance. To the best of my knowledge, there is no published work on the causal effect of over 100 European LEZ on aggregate economic performance.

2 Research Questions

Main question:

- What was the effect of the application of Low Emission Zones (LEZ) on German cities economies and their labour market indicators?

Complementary questions: *(subject to the adequacy of methods and time constraints)*

- Is the reduction of pollution a mediator of this effect and how much it influences the final economic output?
- Which sectors are more affected by the policy?
- What are the relative effects of the different stages of LEZ in Germany?
- What would be the effect of a "German" LEZ in other German or European cities that have not applied it?

[1]Communication from the EC, "A Europe that protects: Clean air for all", accessible here: `https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:52018DC0330&from=GA`

3 Data collection strategy

For this project I need data for treated regions (German cities that applied a LEZ) and a pool of control regions (German or other European cities that have not applied any similar measure) on: (1) Sufficient pre- and post-intervention aggregate data on outputs and predictors of outputs both to test the validity of the identification strategy and be able to see the short and mid term effects of the intervention. (2) Detailed description of the application of policies for all cities considered to correctly assign treatment and create a carefully selected control pool, clean of any similar intervention.

The data has been already gathered from different sources and will be aggregated by geographical location. First, Eurostat's collection of regional statistics available for NUTS regions[2] (from 2000 to 2018 and covering the whole of the EU) provides yearly statistics for the main dependent variables such as GDP, GVA per sector and labour market statistics. Additionally, Eurostat provides local data on predictors and controls such as investment, educational level, science and technology statistics (trademarks and patents), business outputs and demographics.

Secondly, the implementation of LEZ in Germany is well documented by the the German Environment Agency (Umweltbundesamt - UBA). Additionally, data on the implementation of LEZ and similar policies in European regions has been gathered from specialised databases such as *UrbanAccessRegulations.eu* (linked by the UBA and financed by the EC) and the "Green Zones" mobile application that informs professional carriers and drivers on the state of urban access regulations and LEZ in Europe. The data are freely available in their web page and public App although it needed to be scrapped and re-structured.[3] Public information and past studies on policies will help complete and review these external data sources. Finally, local air quality data will come from satellite-based analysis from van Donkelaar et al. (2016) and air stations data from the AirBase of European air quality e-reporting (EEA) with access to the completeness of public air monitoring stations in the European Union (from 3.300 stations in the year 2000 to 8.500 in 2020). This data will be de-weathered using the usual control variables (such as the ones use by Gehrsitz (2017) or by specialized R packages such as `deweather`. An extensive summary of the potential variables and an illustration of the NUTS regions can be found in Table 1 and Figure 2 in the appendices.

[2]NUTS, or Nomenclature of Territorial Units for Statistics, is a geographical code to reference the subdivisions of countries. Granularity varies by country but its especially good in Germany where it tends to follow natural city boundaries.

[3]Neither of them have restrictions to web scraping in their web pages.

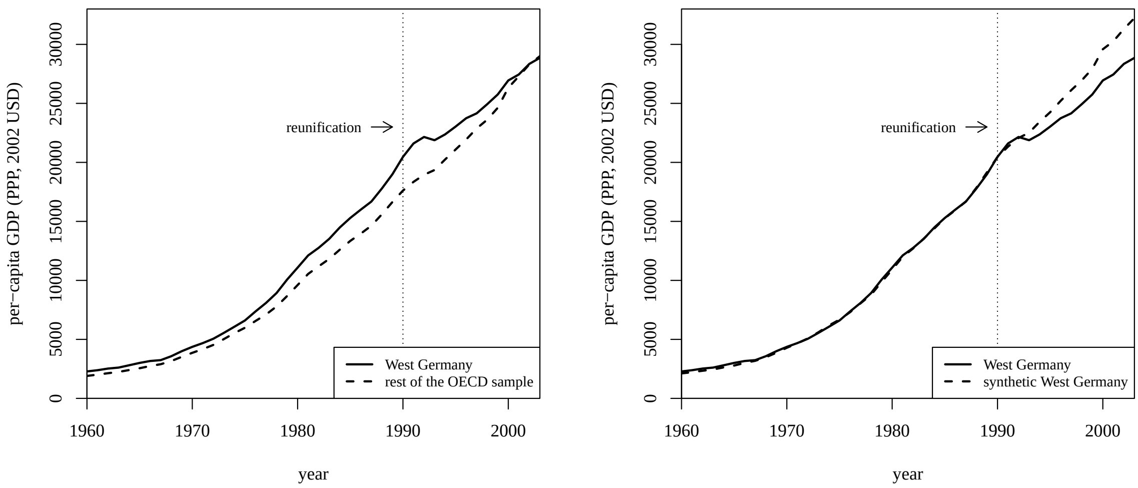
4 Data Analysis strategy

To answer the main question on the effect of LEZ in the city's various economic outputs I intend to use a Synthetic Control Method (SCM) such that the effects in each treated region can be quantified by constructing a synthetic control from all untreated regions both from Germany and the rest of the European Union. This method was introduced in Abadie and Gardeazabal (2003) to study the effect of terrorism in the Basque Country's macroeconomic performance and is extensively described and expanded in Abadie et al. (2010), Abadie et al. (2015) and Abadie (2019).[4] Even if the SCM has not yet been applied to cities' LEZ, previous related research has used very similar techniques. For example, Wolff (2014) and Gehrsitz (2017) applied differences-in-differences (DID) to estimate the causal effect of German LEZ in local air quality.

The SCM is similar from DID, both lay their main identification requirement on having similar trends before treatment and avoid the need of assuming an exogenous treatment assignment. In contrast, although DID allows for the presence of constant unobserved confounders (given they are constructed by taking time differences), the SCM also allows the effects of confounding unobserved characteristics to vary with time (Abadie et al., 2010).

The SCM tries to avoid ambiguity on how comparison units are chosen and account for the uncertainty that they will indeed reproduce "the outcome trajectory that the affected units would have experienced in the absence of the intervention or event of interest" (Abadie et al., 2010). It does it by creating a synthetic control from a weighted average of non-treated units such that it best follows the pre-treatment path of the treated unit and it is as similar as possible in some major predictors of the output. As an illustration of the methodology we can see the example of Abadie et al. (2015) where they created a synthetic control of West Germany to quantify the effects of Germany's reunification in its GDP. We can see the weights that construct the synthetic West Germany from the pool of other OECD members in Table 2, its resemblance in characteristics to the real West Germany in Table 3 and how closely the pre-treatment period is for both synthetic and real West Germany at Figure 1.

[4]Multiple methodologies build on the SCM and could be used in this research, some examples are Abadie and L'Hour (2019) where they include a penalisation term for pairwise differences on characteristics, the Generalized Synthetic Control Method that applies the methodology to multiple treated units (Xu, 2017) and Bayesian structural time-series models (Brodersen et al., 2015) developed in Google which uses other Machine Learning procedures to estimate the counterfactual and its credible interval. All 3 of them have author-developed packages in R or Python.



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

(b) West Germany and its synthetic control

Figure 1: 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).

The SCM is especially appealing for comparative case studies for its transparency and theoretical foundations: (1) All estimations are done within the support of the data (no extrapolation) given it is constructed as a weighted average of control units. (2) We can clearly see the differences in pre-treatment paths and characteristics between treated and synthetic control making possible to assess its internal validity. This allows us to make all decisions regarding the set of controls and predictors by looking at the pre-treatment fit with a measure such as Mean Squared Prediction error (MSPE). Given we don't need access to post-treatment data, we are safeguarded against specification searches and p-hacking. (3) We know the weights of the control units that make the synthetic control, allowing us to evaluate its validity as a control.[5] Inference and statistical significance tests are either based on permutations such as in Abadie et al. (2010) or, if multiple applications of the method for control units are not possible, a test is derived from the ratio of post-intervention fit relative to the pre-intervention fit.

I intend to use the application of the 58 LEZ applied in Germany in the last 12 years (available in Figure 3) as treatment to calculate both the heterogeneity of treatment effects and the average treatment effect on the treated. This gives a range of 8-18 years of pre-treatment data to create the synthetic controls and evaluate their fit. The control pool will be constructed from all European cities of similar size and economic predictors as the treated cities and have not applied similar measures.

[5]See tables 3 and 2 for illustrations from Abadie et al. (2015).

4.1 Main Analysis

The main result would be the effect of LEZ in GDP. The effects on the labour market are especially relevant and will be modelled by decomposing the overall effect, allowing to immediately test for inconsistencies in the results.

Given $GDP \equiv \frac{GDP}{Hours\ worked} * \frac{Hours\ worked}{Employed\ pop.} * \frac{Employed\ pop.}{Working\ age\ pop.} * \frac{Working\ age\ pop.}{Population} * Population$, then the main causal effect to estimate, its decomposition on labour market outputs and their respective interpretation are:

$$\overbrace{\frac{\partial ln(\text{GDP})}{\partial \text{LEZ}}}^{\text{Main effect}} = \overbrace{\frac{\partial ln(\text{GDP/Hours worked})}{\partial \text{LEZ}}}^{\text{Effect on productivity}} + \overbrace{\frac{\partial ln(\text{Hours worked/Employed pop.})}{\partial \text{LEZ}}}^{\text{Effect on absentism or temporality}} +$$
$$\underbrace{\frac{\partial ln(\text{Employed pop./Working age pop.})}{\partial \text{LEZ}}}_{\text{Effect on employment}^{6}} + \underbrace{\frac{\partial ln(\text{Working age pop./Population})}{\partial \text{LEZ}}}_{\text{Effect on the proportion of working age population}} +$$
$$\underbrace{\frac{\partial ln(\text{Population})}{\partial \text{LEZ}}}_{\text{Effect on population}}.$$

The main effects for each industry will be estimated together with other economic outcomes. This will help understand which sectors are more affected by a LEZ. Additional variables might include business growth, number of patents published, education levels (human capital), investment and pollution. Results will be aggregated across cities to produce measures of Heterogeneous Treatment Effects (HTE) to investigate possible city characteristics that correlate with higher treatment effects such as the strength or stage of a LEZ.

4.2 Mediation analysis

To answer how pollution mediates the final effect of the policy I plan to use the Mediation Analysis Synthetic Control (MASC) introduced in Mellace and Pasquini (2019) [7]. To briefly explain their methodology I need first to set some bases on potential outcomes notation. For a given time t, unit i, a binary treatment $D \in \{0,1\}$ and outcome Y_{it}, the set of values of the mediator are defined as $M_{it}(D)$. For example, a LEZ could be the treatment D, GDP could be the outcome Y_{it} and pollution could be a potential mediator $M_{it}(D)$ that depends on the treatment. Finally, the set of potential outcomes are defined as $Y_{it}(D, M_{it}(D')) \equiv Y_{it}^{D,D'}$ for $D, D' \in \{0,1\}$ given they depend both on the treatment and mediator.

[6] Here I am having "Working age population" which is only a proxy of active population. This is due to lack of granular data on the subject and will be improved if possible with NUTS2 data and NUTS3 census data in 2001.

[7] Although this is still a working paper, both the authors of MASC and fellow academics believe that it suitable for this research. I am in contact with the authors and have been given access to their code in R.

MASC creates an estimate of $Y_{it}^{0,1}$ by "re-weighting the control unit post-intervention outcomes by choosing weights that minimize the distance between treated and control pre-intervention observable characteristics as well as post-intervention values of the mediator" (Mellace and Pasquini, 2019). For example, they would compare the actual GDP of Berlin with the synthetic control that follows best its pre-LEZ GDP and its post-LEZ pollution, looking at what would have happened to Berlin in the absence of intervention but with the mediator value characteristic of the intervention: $Y_{it}(D = 0, M_{it}(D' = 1))$.

With the estimate of $Y_{it}^{0,0}$ from the unmodified SCM and the $Y_{it}^{1,1}$ from the realised output path of the treated region, Mellace and Pasquini (2019) define the direct effect as $Y_{it}^{1,1} - Y_{it}^{0,1}$, the indirect (or mediated) effect as $Y_{it}^{0,1} - Y_{it}^{0,0}$ and the total effect as $Y_{it}^{1,1} - Y_{it}^{0,0}$. Only one additional assumption must be taken to apply MASC: that there is some overlap in the post-intervention values of the mediator between treated and the control pool. To continue with the Berlin example, this implies that some of Berlin controls have similar decreases in pollution as the ones experienced in Berlin after the application of a LEZ. The plausibility of this assumption can be graphically assessed by looking at the overlap in the pre-intervention period between the observed outcome, Y_{it}, and the synthetic outcome $Y_{it}^{0,1}$ as they should be no gap before the intervention (Mellace and Pasquini, 2019).

4.3 Estimating potential treatment effects:

As a methodological and policy contribution I plan to use the large set of treated regions to reverse the mechanism of the SCM and use it as a *"Synthetic Treated Method"* to estimate $Y^{1,1}$ and the potential treatment effect of a LEZ in cities that have not applied it. In other words, it will use the pool of treated regions to estimate a synthetic treated for a given control region.

After extensive research on the SCM and their similar methods I have not found this application of the SCM in the literature. If my understanding is correct, no further assumptions are needed and the properties of the classical SCM would apply. A natural case study to test this methodology will be the city of Hamburg (who is the largest German city that has not yet applied a LEZ) although other large European cities are also candidates to be studied.

4.4 Requisites, assumptions and robustness tests

Following technical and practical guidance from Abadie et al. (2010) and Abadie (2019), careful thought has been given to the needed contextual requirements and assumptions of the SCM. They are discussed below.

Identifying requirements:

1. **Sizeable effect:** To be able to identify a treatment effect, its size should be bigger than the individual transitory shocks of regional outcome variables. From preliminary inspection of the data I expect individual transitory shocks to be around 0.5-2% of regional GDP per capita[8]. Regarding estimates on the effect of LEZ on GDP the German pro-business Institute for Retail Research estimates a 7% decrease in customers in stores located within a city centre after the introduction of a LEZ (Lindstaedt, 2009), in contrast, a Transport For London study based of first differences found no significant effects (TFL, 2006). I expect the mediated effect pollution reduction associated with the introduction of a LEZ to be around 1% of GDP pollution given the estimates of Dechezleprêtre (2018) and Gehrsitz (2017).

2. **Non interference between units/cities:** I guide myself with the research done by Wolff (2014) and Gehrsitz (2017) on the effect of German LEZ on pollution, health and vehicle composition to understand the possible spillover effects present within and between German cities. A summary of their findings is as follows: (1) Wolff (2014) concludes that the application of a LEZ also reduces pollution in surrounding areas but this is only significant with big and strict LEZ . Gehrsitz (2017) finds a non-significant effect on pollution reduction in surrounding areas of a LEZ. (2) Wolff (2014) shows that the application of a LEZ correlates with a change towards cleaner vehicles and cities close to it also seem to experience these changes. The correlation is close to a 1-to-5% change in the vehicle composition of a nearby city. Nevertheless, Gehrsitz (2017) looks for a causal effect on pollution reduction and concludes that for a given city "the introduction of an LEZ in a nearby city does not appear to translate into reductions in fine particulate pollution." and adds that his results "indicate that any violations of the SUTVA due to spillovers are unlikely to induce substantial bias into the main results". In conclusion, some spillovers are possible in very specific cases for the outskirts of a large LEZ (that will be included in my NUTS3 regions), but unlikely and economically insignificant for nearby cities. This is crucial information given close cities might be especially good controls if these spillovers are not present.

[8] If the noise in the outcome variables is relatively high, it's possible to use de-noising techniques such as the ones proposed by Amjad et al. (2019).

3. **Valid comparison group:** To construct it I will create a set of European cities that have not applied similar measures or suffered large idiosyncratic shocks during the study period, avoiding biases from confounders and interpolation.[9] I will exclude cities that either suffer for large shocks on aggregate GDP and pollution or are listed in the UrbanAccessRegulations and "Green Zones" databases. Finally, I plan to perform robustness tests excluding German cities that have applied other Environmental Action Plans.

4. **No anticipation:** LEZ in general, and also in Germany, are usually publicised before being enacted specifically to incentivise the public to upgrade their vehicles. This will be accounted by creating an "announced" period, and setting it as the start-of-treatment date in the SCM as recommended in Abadie (2019).

Robustness and diagnosis checks:

1. As documented in Abadie (2019), the main two robustness tests needed for SCM are regarding:

   (a) The choice of units in the donor pool, for which I will restrict it to cities outside a 50-100km radius from a LEZ or inside the same NUTS2 region as the treated LEZ and unite the Rhine-Ruhr metropolitan area as an unique city. Additionally, I plan to perform a leave-one-out re-analysis to check if the inclusion of any individual controls is driving the results of a given city.[10]

   (b) The choice of predictors of the outcome variable, given they specify which macroeconomic variables the SCM should follow more closely in the pre-treatment period. I will closely follow the predictors from Abadie and Gardeazabal (2003) and Abadie et al. (2015) as I am also studying the effects on overall economic performance. Furthermore, I will test how different combinations of them reduce or increase the pre-treatment RMSE and choose accordingly.

2. Finally, in-time placebo treatments as in Abadie et al. (2015) will be done years before the announcement of the LEZ plans to test if highly forward-looking agents decide to change their vehicles even before the city announcing its plans for a LEZ.

[9] To control for interpolation biases Abadie and L'Hour (2019) propose including a penalty term to the objective function that depends on the discrepancies between the characteristics of the treated unit and the units included in the synthetic control. The code is available on their GitHub.

[10] This is done by re-computing the SCM estimates each time without one control that helped create the synthetic control. If a control strongly changes the estimates it might have probably had idiosyncratic shocks during the time of the study.

5 Potential impact and relevance of the study

This research can provide a comprehensive answer to an already pressing question for local authorities, academics and the broad public. The study results can be used to better understand the policy's effects by providing specific estimates for the effect of German LEZ in each city's economy and their labour inputs. All of this accounting for the strength of the restrictions imposed, city-specific characteristics and the mediator role of pollution reduction. Individual cases and the standardisation of treatment will allow to look at the heterogeneity of treatment effects and theorise on the city characteristics that might drive it. These estimates and conclusions will try to help construct more effective and fair public policies on LEZ that take into account the results in similar cities. Additionally, the results will be of especial interest to policy makers and business leaders as they investigate local short-term effects that concerns them directly.

The use of a newly developed methodologies such as the Mediation Analysis Synthetic Control will provide authors and academics with more examples of its use to judge their consistency and adequacy to different research questions. My introduction of a new way of looking the SCM to estimate potential treatment effects intends to further increase the toolkit available of program evaluation techniques with a new methodology.

When concluded, the results should provide a significant and novel contribution that informs pressing public policy on LEZ and air pollution control and works as an example of the application of novel techniques. They could also promote further research on the potential economic effects of LEZ in low- and middle-income countries, especially in those that are highly growth-dependent such as China and India, where the costs of air pollution appear to be very high and policy advice is much needed.

6 Limitations and contingency plans

Limitations of the results are derived from assumptions of the model, its functional form and the data available. The asymptotic properties ans bias bounds of the model are studied in Abadie et al. (2010) and show that a combination of few pre-treatment periods, large transitory shocks and a large and unfiltered control pool will result in biases if the data follows a linear factor model. German cities have sufficient pre-treatment periods and the control pool will be carefully filtered, but I can't control the size of transitory shocks that could obscure economically significant effects of 0.5-2% of GDP and render non statistically significant estimates. Luckily, the robustness and diagnosis tests will signal the quality of the fit. Regarding external validity, I believe it would be safe to interpret the results in an European context with restrictions similar to the ones in German LEZ and especially good if city-specific characteristics could be matched to one of the treated units. Nevertheless, it would be hard to extrapolate results to developing countries where, for example, individuals have less disposable income to change a vehicle to a less polluting one.

Regarding contingency plans, if there are no visible problems with the credibility of the synthetic control but the individual transitory shocks are big enough to obscure significant policy effects I can use de-noising techniques such as the ones proposed by Amjad et al. (2019). Additionally, if from the robustness and diagnosis checks it is clear that some synthetic controls are not credible (do not follow the pre-intervention path of the treatment, or not sufficiently similar in relevant metrics) I can both exclude those LEZ from the analysis, do the overall analysis with a similar methodology such as Difference in Differences (as Gehrsitz (2017)) or find other case study and data to estimate the policy effect.

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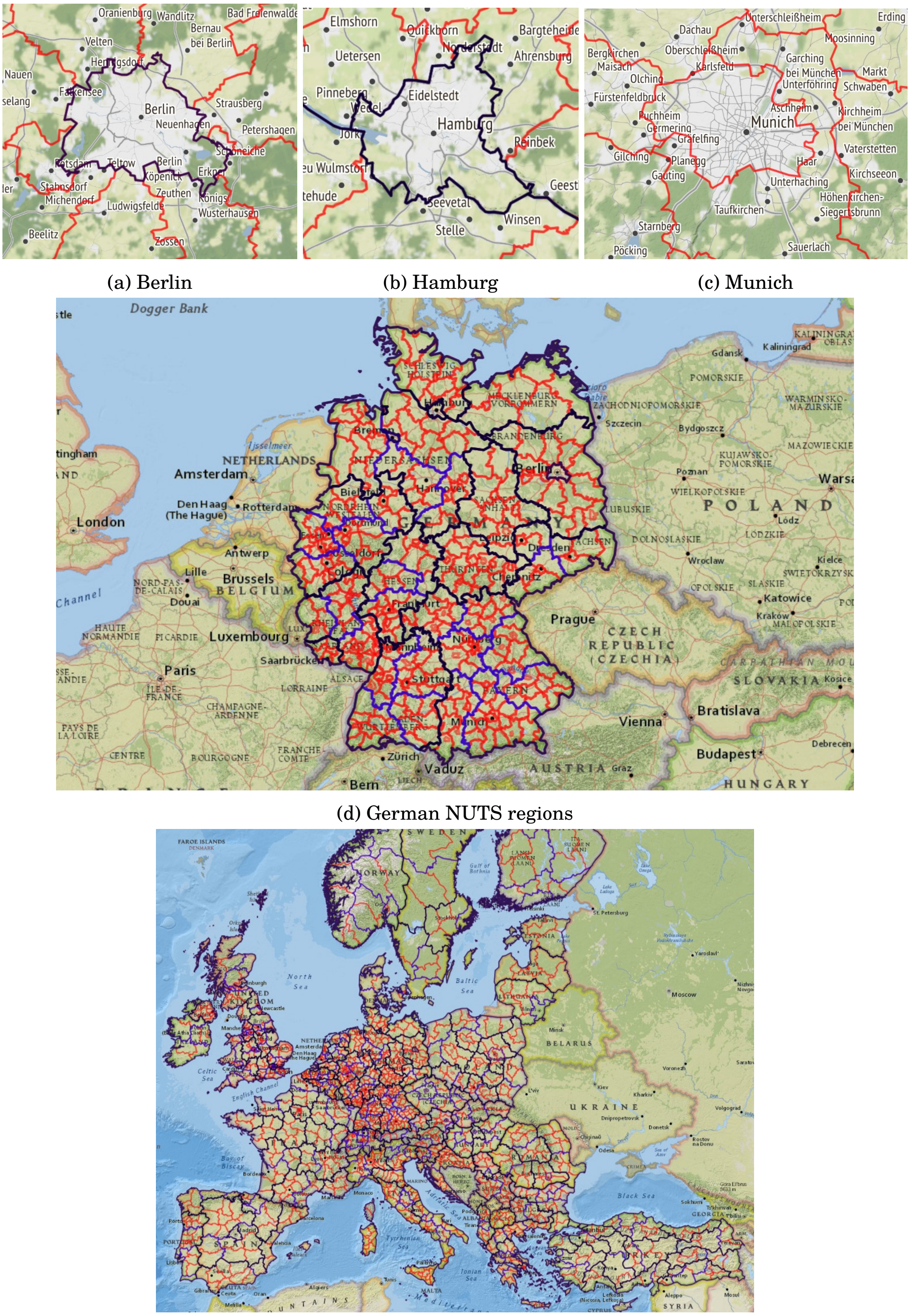
Appendices

Variable	Coverage	Geography	Start	End	Delta	Source
Outcomes (Y):						
GVA at basic prices by NACE activites	EU	NUTS 3	1995	2017	1 year	Eurostat
GDP	EU	NUTS 3	2000	2017	1 year	Eurostat
GDP at current prices	EU	NUTS 4 (LAU 1)	2000	2017	1 year	Eurostat
Spatial variation (X):						
Boundaries of LEZ zones	EU	georeferenced	Most recent			urbanaccessregulations.eu
Boundaries of LEZ zones	EU	georeferenced	Most recent			"Green-Zones" App
Boundaries of LEZ zones	Germany	georeferenced	Most recent			"Umweltzone" App
Boundaries of LEZ zones and details on their implementation	EU	Complete	All	All	1 day	Official and legal documents
Boundaries of LEZ zones and details on their implementation	EU	georeferenced	Partial	Partial	Varies	openstreetmap.org
Details on LEZ's implementation	Germany	Complete	2008	2020	1 day	Umweltbundesamt
Details on LEZ's implementation	Germany	"Described"	All	2017	1 month	Gehrsitz (2017) and Wolff (2014)
Predictors and secondary outcomes:						
Employed persons by NACE	EU	NUTS 3	1995	2017	1 year	Eurostat
1000 Hours Worked	EU	NUTS 2	2000	2017	1 year	Eurostat
Economically active population by sex and age (imperfect)	EU	NUTS 4 (LAU 1)	2000	2017	1 year	Eurostat
Unemployed persons/rate by Age (imperfect)	EU	NUTS 4 (LAU 1)	1995	2017	1 year	Eurostat
Total and active population by sex, age, employment status, residence one year prior to the census	EU	NUTS 3	2001	2001	1 year	Eurostat Census
Population by age and sex	EU	NUTS 3	1990	2018	1 year	Eurostat
Investment	EU	NUTS 2	1995	2017	1 year	Eurostat
Employer business demography by NACE Rev. 2	EU	NUTS 3	2008	2016	1 year	Eurostat
Employer business demography by size class	EU	NUTS 3	2008	2016	1 year	Eurostat
Business demography and high growth enterprise by NACE Rev. 2	EU	NUTS 3	2008	2016	1 year	Eurostat
Business demography by size class	EU	NUTS 3	2008	2016	1 year	Eurostat
Community design (CD) applications	EU	NUTS 3	2003	2016	1 year	Eurostat
Patent applications to the EPO by priority, IPC, sections and classes	EU	NUTS 3	1977	2012	1 year	Eurostat
High-tech patent applications to the EPO by priority year	EU	NUTS 3	1977	2012	1 year	Eurostat
Patent applications to the EPO by priority year	EU	NUTS 3	1977	2012	1 year	Eurostat
Nº of vehicles by emission category	Germany	districts/cities	2008	2018	1 year	Kraftfahrtsbundesamt
Mediator:						
PM2.5 mean concentration	EU	0.01^{o} x 0.01^{o}	2000	2017	1 year	van Donkelaar et al. (2016)
PM2.5 concentration	EU	$10km^2$	2008	2015	1 day	CAMS
Air pollutants concentration summary	EU	Weather Stations	2000	2018	1 year	EEA
Air pollutants concentration	EU	Weather Stations	2000	2018	1 day	EEA
Other variables (mostly control):						
Number of deaths	EU	NUTS 3	1990	2017	1 year	Eurostat
Population change	EU	NUTS 3	2000	2018	1 year	Eurostat
Land use (degree of urbanization)	EU	NUTS 3	2015	2020	5 years	JRC
Live births	EU	NUTS 3	1990	2017	1 year	Eurostat
Area (m^3)	EU	NUTS 3	1990	2015	1 year	Eurostat
Live births by age of the mother	EU	NUTS 3	1990	2017	1 year	Eurostat
Fertility rate	EU	NUTS 3	1990	2017	1 year	Eurostat
Age dependency ratio by age class	EU	NUTS 3	2014	2018	1 year	Eurostat
Young age dependency ratio	EU	NUTS 6 (city)	2000	2018	1 year	Eurostat
Share of transport means to work (imperfect)	EU	NUTS 6 (city)	2001	2012	1 year	Eurostat
Cars/1000 persons (imperfect)	EU	NUTS 5 (LAU 2)	2002	2012	1 year	Eurostat
Shape files:						
NUTS and LAU regions	EU	NUTS and LAU	All	All	All	Eurostat
Functional Urban Areas	EU	NUTS and LAU	All	All	All	Eurostat
Metropolitan Areas	EU	NUTS and LAU	All	All	All	Eurostat

Table 1: Variables for the analysis with their source, geographic and time coverage.



(a) Berlin

(b) Hamburg

(c) Munich

(d) German NUTS regions

(e) Main coverage of NUTS 3 zones

Figure 2: Main coverage of NUTS zones across Europe and Germany, with examples of cities. Borders of NUTS 1, 2 and 3 regions are coloured in black, blue and red, respectively.
Source: Eurostat and own work.

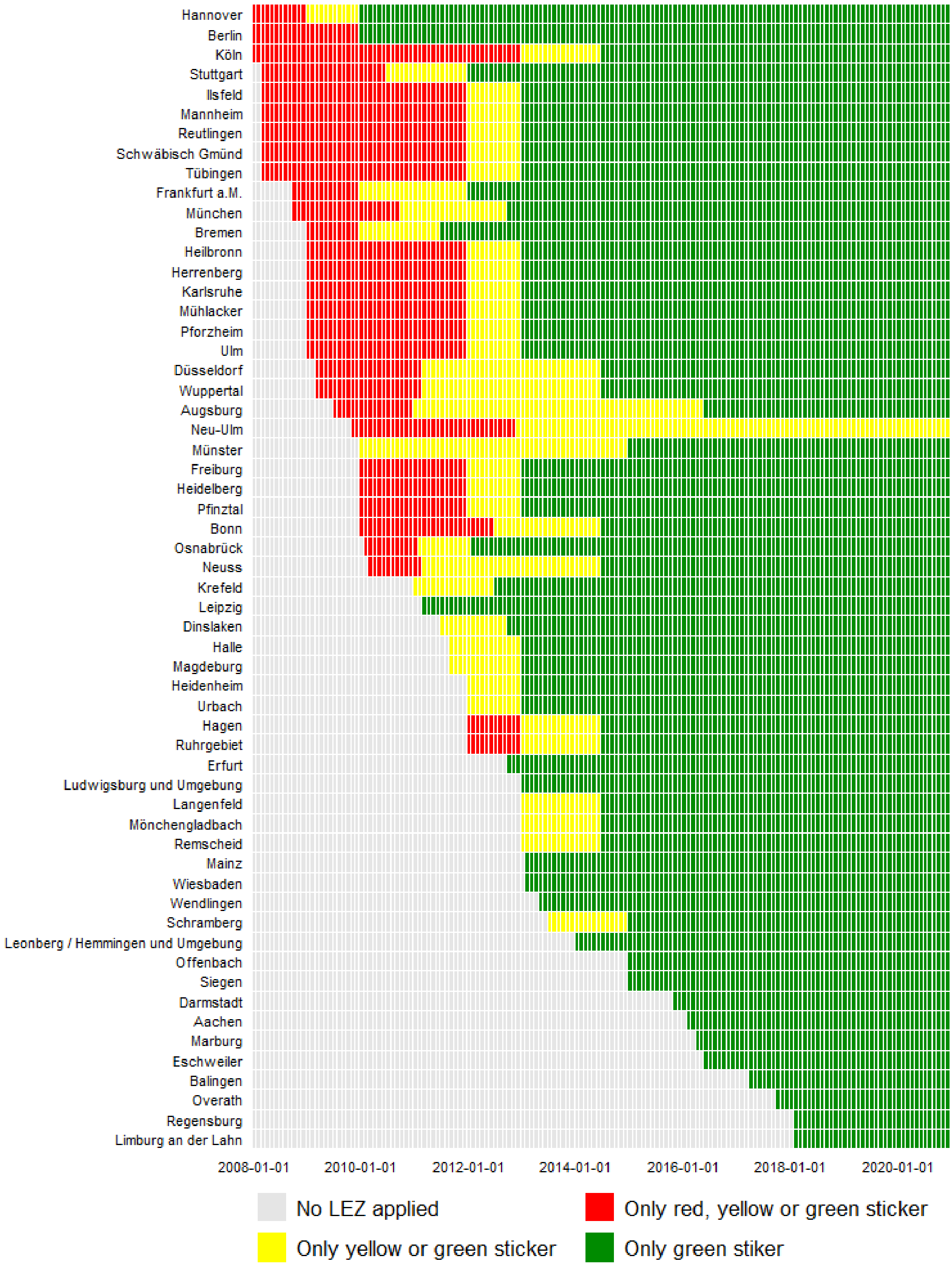


Figure 3: Application of LEZ in Germany by category of environmental stickers allowed and month of the year.
Source: Umweltbundesamt and my own work.

Countries	Weights
Australia	-
Austria	0.42
Belgium	-
Denmark	-
France	-
Greece	-
Italy	-
Japan	0.16
Netherlands	0.09
New Zealand	-
Norway	-
Portugal	-
Spain	-
Switzerland	0.11
UK	-
USA	0.22

Table 2: Weights of different countries in the control pool that construct the synthetic Germany in Abadie et al. (2015). This helps us judge the plausibility of the control group and avoid spurious correlations.
Source: Abadie et al. (2015).

	West Germany	Synthetic West Germany	Rest of OECD Sample
GDP per-capita	15808.9	15802.2	8021.1
Trade openness	56.8	56.9	31.9
Inflation rate	2.6	3.5	7.4
Industry share	34.5	34.4	34.2
Schooling	55.5	55.2	44.1
Investment rate	27.0	27.0	25.9

Table 3: Here we can see the resemblance in characteristics of West Germany and its synthetic control compared to the mean of the rest of OECD sample..
Source: Abadie et al. (2015).