DOCTORAL THESIS

Alternative approaches for counterfactual evaluation in the presence of a few units

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Knowing "what cause what" makes a big difference in how we act.

Judea Pearl

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Introduction

In everyday life, social and economic actors think in causal terms. Identifying and quantifying the causes behind an effect is one of the aspects driving human behavior. Knowing that if the cause had not occurred then the effect would not have either, is crucial in policy evaluation processes.
In the XVIII century, the philosopher David Hume in 'A Treatise of Human Nature' criticized how, only based on our experience, we have often been led to believe that when an event regularly follows another, a cause-effect relation is established. The experience often helps, but sometimes it is not enough. In the 'Enquiry Concerning Human Understanding', Hume identifies three elements of the causation idea: (a) spatial/temporal contiguity, (b) temporal succession, and (c) constant conjunction. According to Hume, it is the constant conjunction that makes the difference in determining a causal effect.
Although the rooster's crowing is connected to sunrise, we cannot claim that the rooster's crowing causes the sunrise. Therefore, Hume does not take into account the risk of mistaking simple associations or correlations with the cause-effect relationship.
Despite the complexity, how can we approach this issue?
A statistical solution to quantify a cause-effect relation is the counterfactual approach. The counterfactual approach aims to measure the effect of the cause[1] by comparing what happens (factual situation) with what would have happened if the intervention had not been implemented (counterfactual situation). The idea was first discussed by Neyman, 1923 and Neyman and Iwaszkiewicz, 1935 in the field experiments and then generalized by Rubin, 1974 with what would then be defined as the Rubin Causal Model (RCM).
The RCM introduces the potential outcomes concept: each unit in a population ($j = 1, 2, ..., J$) can be exposed or not to treatment. The outcome (Y) measures the response to the cause. It can take two potential values, one that

[1]The terms cause, event, intervention, or treatment will be used interchangeably.

would be observed if the unit was exposed to the intervention (Y^I) and another that would be observed in the absence of exposition (Y^N). Then, the causal effect (θ) for a generic unit j is given by the comparison between the two potential outcomes, as follows:

$$\theta_j = Y_j^I - Y_j^N. \tag{1}$$

Unfortunately, only one of the potential outcomes can at most be realized and thus observed for the same unit at the same time. This is 'The Fundamental Problem of Causal Inference', formalized by Holland, 1986 that can be expressed in the following observational rule:

$$Y_j = Y_j^I(D_j) + Y_j^N(1 - D_j), \tag{2}$$

where D_j is the treatment variable, equal to 1 if unit j is exposed to the intervention, and equal to 0 otherwise.

Given that we cannot directly observe the factual and the counterfactual situations for the same individual, we can argue it is a problem of missing data. It is possible to resort to a statistical solution, estimating the average effect of the treatment for the population, i.e., comparing the difference in means between a group of units exposed to the intervention (treated group) and a group of units not exposed to the intervention (control group). If the two groups have a similar distribution in the observed and unobserved characteristics, it enables estimating the causal effects to the population level. This is possible in randomized experiments, where individuals have the same possibility to be exposed to the treatment before treatment assignment. In many circumstances, randomized experiments are not possible due to ethical or practical problems or because we would like to evaluate ex-post an effect, i.e., after that treatment occurred. In these cases, we can resort to counterfactual approaches to identify a control group. The first empirical threat to face is selection bias. Because treated and control groups have no similar characteristics, the potential outcomes may depend on the selection of the treated units.

Different statistical methodologies, called quasi-experimental, use observational data and attempt to correct the assignment mechanism by selecting

ex-post a control group as close as possible to the treated one. The choice of the methodology concerns the process selection and the data availability.
Almost all approaches are based on estimating a counterfactual situation for a group of units exposed to the intervention. However, we might be interested in causal effect estimates on one or a few units.
In the policy evaluation context, many policy interventions occur at an aggregate level (cities, regions, states) on one or a few units. In this case, if we have information before and after treatment both for treated and control units, the best solution is the Synthetic Control Method (SCM).
It was proposed for the first time by Abadie and Gardeazabal, 2003 with the idea of determining the potential outcome in the absence of intervention as a *synthetic control*, i.e., a unit that closely reproduces what would have happened to the treated unit in the absence of the intervention. The synthetic control is built by a linear combination of untreated units, known as *donor pool*, similar to the treated one in the pre-treatment characteristics. The weights given to each unit in the donor pool are chosen to minimize the distance between pre-intervention outcomes and observable characteristics of treated and controls. If the treated and the synthetic units are equal in the pre-treatment, the difference in the post-treatment is attributable only to the treatment.
SCM was defined by Athey and Imbens, 2017 as 'the most important innovation in the policy evaluation literature in the last 15 years'. Its transparent nature makes it easily interpretative such that to become one of the most popular approaches used not only in many fields in economics but also in social science, biomedical disciplines, engineering, etc.
Based on RCM, the SCM is built on Stable Unit Value Assumption (SUTVA) that includes the hypothesis of no interference between units so that intervention on one unit does not affect the others. Given spatial and social linkages between economic agents, it appears an unrealistic assumption in many empirical applications.

The dissertation is part of this flourishing literature that estimates the causal effect of policy intervention in a panel data setting with only one or a few treated and control units. The thesis focuses on improving the estimate accuracy and making the issue of the methodology more suited to real applications, by giving methodological and empirical contributions. It is possible

to do this considering that units can be affected directly or indirectly by the treatment or disaggregating units to catch heterogeneity.
Particularly, the thesis is composed of three chapters, described briefly below. All refer to the SCM literature. The first one introduces a novel methodological proposal, the second one an empirical application of this proposal, the third one with an application of recent methodological advances in the SCM field.

The **first chapter** gives a methodological contribution.
It introduces a novel and intuitive synthetic control modification that allows including units potentially affected directly or indirectly by an intervention in the donor pool: the inclusive synthetic control method (iSCM).
It is advantageous in two scenarios:

1. For application with multiple treated units. When some of the treated units need to be included in the treated unit's donor pool, i.e., without including other treated units, the fit is too poor to identify a good counterfactual.

2. For applications in which some of the units in the donor pool might be affected by spillover effects. As discussed by Abadie, 2021, in some circumstances, spillover effects are possible, and it is a strong assumption to presume they do not exist, which may lead to a biased estimate.

We can safely include affected units in the donor pool and then eliminate post-intervention effects in both scenarios. In the second scenario, iSCM also allows us to estimate the spillover effects.
The iSCM can be easily implemented using the standard synthetic control algorithm or any new estimation method available in the literature. Moreover, it only requires that the standard SCM assumptions be valid in the absence of post-intervention effects and the presence of at least one *pure control unit*, i.e., one unit potentially unaffected by the intervention.

The **second chapter** gives an empirical contribution.
To explain how SCM works Abadie et al., 2015 and Abadie, 2021 investigate the economic effect of the 1990 German reunification on West Germany. They use a panel set of 16 OECD countries to build a synthetic West Germany. In

one comment, the authors affirm that it could have had negative spillover effects on Austria's economic growth because West Germany diverted demand and investment from Austria to East Germany. This would imply that the big negative effect they found is likely to be an upper bound of the true effect. As it is arguably important to include Austria in the donor pool, the iSCM is very well suited for this empirical application.
We illustrate how to use iSCM by re-estimating the economic impact of Germany reunification on West Germany's GDP per capita, allowing for spillover on Austria. We confirm Abadie et al., 2015 expectations about the potential direction of the spillover effect from West Germany to Austria.

The **third chapter** gives an empirical contribution allowing with cutting-edge methodology in a setting with a few units and fitting two kinds of literature: the one on Optimal Currency Area (OCA), and on the other hand, the one dealing with the core-periphery issue.
In particular, we investigate the economic impact of joining the euro area for the latecomers, i.e., the countries that adopted the euro after 2002, verifying how this can change in the case of a recession. Differently from previous literature, we use NUTS-2 regions as units of analysis. This novelty allows us to improve the estimate accuracy and better investigate the theoretical predictions on currency union's impact. Using a recently developed approach by Hazlett and Xu, 2018 from SCM literature, i.e., the kernel balancing approach, we estimate the overall and disaggregated impact of joining the euro area. Overall, we find that the euro's adoption brought about a small positive effect, which was, however, dampened by the Great Recession. Individual regional estimates suggest heterogeneous returns with positive benefits accruing to the core regions.

The study conducted in the first and second chapters presented in the dissertation comes from a collaboration with Prof. Giovanni Mellace from Southern Denmark University. The study presented in the third chapter was conducted in collaboration with Dr. Augusto Cerqua and Prof. Guido Pellegrini. The whole thesis was supervised by Prof. Guido Pellegrini and Dr. Augusto Cerqua.

Chapter 1

The inclusive synthetic control method

This chapter has a two-fold purpose: it presents the literature review on Synthetic Control Methods and no interference assumption and introduces the inclusive Synthetic Control Method, a novel and intuitive synthetic control modification that allows including units potentially affected directly or indirectly by an intervention in the control group.

1.1 The Synthetic Control Method

The synthetic control method (SCM) introduced by Abadie and Gardeazabal, 2003 and further developed by Abadie et al., 2010, and Abadie et al., 2015 allows estimating the causal effect of a policy intervention in settings where only a few treated and control units are observed over a long time period.
The problem of estimating the causal effect (θ) is equivalent to the problem of estimating the potential outcome in the absence of intervention (Y^N).
Usually, comparative case studies use one or a small number of control units with similar characteristics to the treated unit at the time of the intervention to solve the problem. Nevertheless, when the treated unit is one, it generally consists of an aggregate unit (e.g., regions or countries), so it is hard finding a control unit alone that is a good comparison for it.

Assume we observe $j = 1, ..., J$ units for $t = 1, ..., T$ periods. For each unit j at time t we observe the outcome of interest Y_{jt} and a set of k predictors of the outcome $X_{1j}, ..., X_{kj}$, which often includes pre-intervention values of

Y_{jt}. Without loss of generality, we assume we are interested in the effect θ of an intervention, implemented at time T_0, on the outcome Y of the first unit $j = 1$. Assume that units $j = 2, \ldots, J$ are not affected by the intervention and represent the potential comparison units, i.e., the donor pool.

The idea behind the SCM is to create a 'synthetic' version of the treated unit as a weighted average of the control units to recover his potential outcome in the absence of the intervention Y_{1t}^N in the post-intervention period ($t > T_0$). Namely, Y_{1t}^N is estimated as

$$\widehat{Y}_{1t}^N = \sum_{j=2}^{J} \widehat{w}_j Y_{jt}, \tag{1.1}$$

where $\widehat{w}_j \geq 0$ and $\sum_{j=2}^{J} \widehat{w}_j = 1$. These restrictions on the weights are imposed to avoid extrapolation bias[1].

To estimate the synthetic weights $W^* = (w_2^*, ..., w_J^*)'$, Abadie and Gardeazabal, 2003 and Abadie et al., 2010 propose to minimize the distance between the outcomes and observable characteristics of the treated and the synthetic control in the pre-intervention period, i.e.

$$\widehat{W} = \min_{W} \|X_1 - X_0 W\| = \min_{w} \Big(\sum_{h=1}^{k} v_h (X_{h1} - w_2 X_{h2} - ... - w_j X_{hJ})^2 \Big)^{1/2}, \tag{1.2}$$

where, the $k \times 1$ vector X_1 contains the values of the predictors $X_{1j}, ..., X_{kj}$ for treated unit $j = 1$. The $k \times (J-1)$ matrix $X_0 = [X_2, \ldots, X_J]$ collects the values of the k predictors for the $J - 1$ untreated units. $V = (v_1, ..., v_k)'$ is a set of non-negative constants that reflects the relative important of $X_{1j}, ..., X_{kj}$ as predictors of Y_{1t}^N. Each potential choice of $V = (v_1, ..., v_k)'$ produces a different $W(V)$, determined by the minimizing equation 1.2, subject to the restriction that the weights have to be positive and sum to one. The set V can be chosen in different ways (see Abadie, 2021 for more details).

[1]See, e.g., Doudchenko and Imbens, 2017 for a modification of the standard SCM that allows for negative weights.

The causal effect of the intervention is then estimated as follows:

$$\widehat{\theta}_{1t} = Y_{1t} - \sum_{j=2}^{J} \widehat{w}_j Y_{jt}. \tag{1.3}$$

To justify the use of a linear combination of weights that minimize the distance between the observable characteristics of the treated and the control units in pre-intervention, Abadie et al., 2010 study the bias properties of SC estimators for the cases when a linear factor model generates the counterfactual[2], as follows:

$$Y_{jt} = \delta_t + \alpha_t Z_j + \lambda_t \mu_j + \epsilon_{jt}, \tag{1.4}$$

where δ_t is a time trend, Z_j is a vector of observed characteristics, μ_j is a vector of unobserved characteristics, α_t and λ_t are coefficients and ϵ_{jt} are zero mean individual transitory shocks.
For a given set of weights W, we have

$$\sum_{j=2}^{J} w_j Y_{jt} = \delta_t + \alpha_t \sum_{j=2}^{J} w_j Z_j + \lambda_t \sum_{j=2}^{J} w_j \mu_j + \sum_{j=2}^{J} w_j \epsilon_{jt}. \tag{1.5}$$

Assume there exists a set of weights W^*, such that $\forall t < T_0$

$$\sum_{j=2}^{J} w_j^* Y_{jt} = Y_{1t} \tag{1.6}$$

$$\sum_{j=2}^{J} w_j^* Z_j = Z_1 \tag{1.7}$$

It is easy to show that under mild conditions, when the number of pre-intervention periods T_0 goes to infinity

$$\widehat{\theta}_{1t} - \theta_{1t} \to 0, \; t > T_0. \tag{1.8}$$

In other words if there exists as set of weights such that $X_1 = X_0 W^*$, i.e. the synthetic control is able to perfectly reproduce the characteristics and the

[2] They also study the case when the counterfactual is generated by a vector autoregressive model showing that the estimator is unbiased under certain conditions.

outcome of the treated unit in the pre-treatment period then the synthetic control estimator bias goes to zero as the number of pre-intervention periods goes to infinity.

However, if $X_1 - X_0\widehat{W}$ is large, even with an infinite number of pre-intervention periods the bias of the SC estimator would not vanish. As the credibility of the synthetic control depends on $X_1 - X_0\widehat{W}$ one needs to be cautious on which units to include in the donor pool. Including control units that have very different pre-intervention characteristics Z_j and/or which we suspect to be different in unobserved characteristics μ_j relative to the treated increases the risk of interpolation bias. This possibility is even higher when the number of control units is large and the pre-treatment period small. Ideally, the treated unit characteristics X_1 needs to lie in the convex hull of the controls units characteristics X_0. However, in most empirical applications it is more plausible to assume that X_1 falls outside but still close to the convex hull of X_0 which should still result in a small bias (see Abadie 2021).

SCM is receiving increasing attention in the literature. Athey and Imbens, 2017 argue that SCM is '...the most important innovation in the policy evaluation literature in the last 15 years'. The easily guessed idea and the transparent construction that allows a quick interpretation lead it increasing popularity enough to be used in a lot of empirical studies, not only in economic fields.
In that sense, several scholars improved upon the original method in different dimensions (see Abadie, 2021 for a recent literature review).
As previously highlighted, an important issue is the bias reduction due to an imbalance in observed characteristics. Although it would seem to play a marginal role relative to pre-treatment outcomes, the predictors Z_j are really important in the prediction of the synthetic. Their exclusion increases the number of factors of μ_j, increasing the bound on the bias. So, one strand of the literature focuses on this.
Abadie and L'Hour, 2019 propose a bias reduction procedure based on introducing a penalty term that reduces pairwise matching discrepancies between the characteristics of the treated and each of the control units and helps avoid interpolation bias. Botosaru and Ferman, 2019 discuss implications of not having perfect covariate balance and provide alternative assumptions under

which SCM can still be used. Kellogg et al., 2020 propose a model averaging method called 'matching synthetic control estimator' that is a convex combination of the synthetic control and matching estimators. Their procedure gives weight to the synthetic control estimator proportional to the risk of having extrapolation bias.

Another strand of the literature focuses on problems related to having an imperfect fit in the pre-treatment period. Ferman and Pinto, 2019 analyze the properties of SCM when the pre-treatment fit is imperfect. Similarly, Ben-Michael et al., 2020 discuss potential problems with SCM and propose an outcome model to estimate the bias. They also consider the staggering adoption setting (Ben-Michael et al. 2019). Doudchenko and Imbens, 2017 allow a better pre-intervention fit, proposing a generalization of the synthetic control, relaxing weight-constraints, i.e., allowing weights to be negative, and their sum to be different to one, and adding a time-constant intercept.

Finally, several contributions focus on generalizing the method and compare it to alternative approaches. Gobillon and Magnac, 2016 compare linear factor models and synthetic controls. Xu, 2017 proposes a generalization to unify synthetic control with linear fixed-effects models. Amjad et al., 2018 propose a procedure based on de-noising the outcomes and imputing the missing values. Arkhangelsky et al., 2019 propose a new synthetic control as a weighted regression estimator with time-fixed effects. Mellace and Pasquini, 2019 show how to use SCM to estimate how much of the total effect of intervention goes through observed intermediate outcomes (causal channels). Athey et al., 2020 use matrix completion techniques to derive a new method that includes synthetic control as a special case.

1.2 Stable Unit Treatment Value Assumption

The SCM implicitly imposed the so called Stable Unit Treatment Value Assumption (SUTVA) (Rubin 1980).

Imbens and Rubin, 2015 using these words to define SUTVA: *'The potential outcome for any unit does not vary with the treatment assignment to other units, and, for each unit, there are not different forms or versions of each treatment level, which lead to different potential outcomes.'*

Therefore, we can distinguish two SUTVA's components:

1. no interference among units;
2. no multiple versions of the treatment.

Now we consider the component of no interference, i.e., the intervention on one unit does not affect the others (Cox 1958), so spillovers effects are ruled out.
Sometimes, researchers assume that spillovers are negligible or select the control group that is more likely unaffected by the treatment to avoid biased estimates of the treatment effect. Unfortunately, other times it appears a very strong assumption, unrealistic in many empirical applications. Ignoring interference can lead to biased estimates and consequently inaccurate policy recommendations and incorrect understanding of data-generating models (Sobel 2006). In such a case, SUTVA may be necessary to relax.
The situations in which no interference assumption is not plausible are different, particularly in policy evaluation context where interactions between units geographically or economically close are common.
Different types of spillover effects can be identified in economic literature. Angelucci and Di Maro, 2016 describe the four main types: externalities, social interactions, context equilibrium effects, and general equilibrium effects. Despite this classification, often, it does not necessarily enable one to distinguish them. But an important issue concerns understanding the design context and hypothesizing which type of spillover effect might occur, but above all which units/group may be affected.
A way to (partially) relax SUTVA is assuming partial interference (Sobel 2006), i.e., interactions between units are only possible in the same group but not between different groups. In such a way, there are: a group directly affected, i.e., receiving the treatment; a group indirectly affected, i.e., influenced by the treatment; and a group unaffected by the treatment.
The identification of which units are indirectly affected, and those are not affected is complex. For example, Cerqua and Pellegrini, 2017 split the affected units into strata about economic and spatial distance. Then, they face the problem of applying a combined approach that involves coarsened exact matching and the difference-in-difference (DiD) estimator to compute

the Average Treatment Effect and the Average Spillover effect on the Affected. Forastiere et al., 2020 also limit the propagation of treatment to immediate neighbors. They define a joint treatment for each unit that is subject to individual treatment and a neighboring treatment and identify the causal estimands as average comparisons of potential outcomes under different values of the treatment of both the unit and his neighbors. They propose a semi-parametric propensity-score-based estimator. A similar study that investigates stratum-specific causal mechanisms was conducted by Huber and Steinmayr, 2019. They consider a SUTVA on an aggregate level, i.e., SUTVA allows for spillover effects between individuals within regions but rules out such effects across regions and propose a DiD approach that relies on common time trends of potential outcomes within strata but across regions. Vazquez-Bare, 2017 identify and estimate the direct and the spillover effects in randomized controlled trials considering partial interference.

As the synthetic control idea is to consider units as similar as possible to the treated, possibly affected by the same regional shock, so to reproduce closely the treated unit, the problem of spillover units becomes even relevant. Including units affected by spillovers can provide bias estimates; on the other hand, excluding them can reduce the quality of the match, risking not finding a 'good' counterfactual. Thus, the recent literature faces the violation of the no interference assumption. In particular, there are two contributions that deal with it.

The first one is in line with the partial interference assumption and it is proposed by Grossi et al., 2020. The authors reduce the donor pool to only units not affected by spillovers. Then, they estimate the effect for the treated unit using a standard SCM with the restricted donor pool and the spillover effects comparing units affected by spillover and the restricted donor pool. Their method is very effective in applications where the restricted donor pool is sufficient to construct a 'good' synthetic control. However, in a setting where the units affected by spillover need to be included in the donor pool, their method would likely produce biased results. Cao and Dowd, 2019 provide a different identification strategy imposing a linear spillover structure, so assuming to knowledge about the spillover effects. Although they derive asymptotically unbiased estimators under certain conditions, their approach restricts effect heterogeneity.

1.3 The inclusive synthetic control method

In the standard SCM only units that are not affected by the interventions are included in the control group.
This might be problematic in at least two scenarios:

1. some of the treated units need to be included in the donor pool for the treated to improve the pre-intervention fit;

2. some of the control units in the donor pool are affected by the intervention indirectly (spillover units).

Our main contribution is to introduce the inclusive synthetic control method (iSCM), a novel procedure that allows us to eliminate post-intervention effects from control units and safely include them in the donor pool. Our procedure does not require modifying the original synthetic control estimator, and all the new recent methods can be used instead. The main additional assumptions required are that the number of 'potentially affected' units is known and that the standard SCM assumptions would hold if there were no post-intervention effects for those units.

Although iSCM only requires the existence of at least one 'pure control' unit, we expect that the quality of our estimator deteriorates if the number of 'potentially affected' units increases. Thus, it is advisable to impose assumptions that limit this number. This is similar to what is done in the literature on spillover effects, where it is often assumed that interactions between units are only possible in the same group but not between different groups (see Section 1.2).

1.3.1 Setting

We now refer to the treated unit (unit 1) as the 'main treated'. We also assume that the set of $j = 2, \ldots, J$ units, previously defined as untreated units, includes $m \leq J - 1$ units (units 2 to m) that are directly or indirectly affected by the intervention ('potentially affected' hereafter), i.e., either other treated units that we would like to include in the donor pool or control units that might be affected by spillover effects from the main treated. We refer to units $m+1$ through J, as 'pure control units' and assume that they are not affected by the intervention at all.

We define the potential outcome (see, e.g., Rubin 1974) Y^I_{1t} as the outcome that the main treated unit would obtain under the intervention at time t. With a little abuse of notation, $Y^S_{jt}, j = 2, \dots, m$ represent the potential outcome that the potentially affected units would get at time t in the presence of the intervention. Finally, we define as $Y^N_{jt}, j = 1, \dots, J$ the potential outcome in the absence of the intervention. We denote the number of pre-intervention periods as T_0, and we define the following two binary indicators:

$$D_{jt} = \begin{cases} 1 & if \;\; j = 1 \;\; and \;\; t > T_0, \\ 0 & otherwise. \end{cases} \tag{1.9}$$

$$S_{jt} = \begin{cases} 1 & if \;\; j = 2, ..., m \;\; and \;\; t > T_0, \\ 0 & otherwise. \end{cases} \tag{1.10}$$

These binary indicators are used to select the main treated and the units that are potentially affected by the intervention, respectively, in the post-intervention period.

Assuming no anticipation effects in the pre-treatment period and that the standard SUTVA holds (partially in the case of spillover effects), we can relate the observed and the potential outcome by the following observational rule:

$$Y_{jt} = Y^N_{jt}(1 - D_{jt})(1 - S_{jt}) + Y^I_{jt} D_{jt} + Y^S_{jt} S_{jt}. \tag{1.11}$$

This implies that in the pre-intervention period, Y_{jt}=Y^N_{jt} for all units, while in the post-intervention period, Y_{jt}=Y^N_{jt} for the pure control units; Y_{1t}=Y^I_{1t} for main treated and Y_{jt}=Y^S_{jt} for the other potentially affected units.

Our parameters of interest are the effect of the intervention for the main treated at time $t > T_0$, denoted by θ_{1t}, and the effects on the other potentially affected units denoted by $\gamma_{jt}, j = 2, \dots, m, t > T_0$, defined as

$$\theta_{1t} = Y^I_{1t} - Y^N_{1t}, \quad t > T_0 \tag{1.12}$$

and

$$\gamma_{jt} = Y^S_{jt} - Y^N_{jt}, \quad j = 2, \ldots, m, \quad t > T_0. \tag{1.13}$$

To identify these parameters, we need to recover Y^N_{1t} and Y^N_{jt} for $j = 2, ..., m$ in the post-treatment period. If, hypothetically, one used the standard SCM as described in Abadie et al. 2010 and included the potentially affected units in the donor pool, the resulting estimate of the counterfactual potential outcome of the main treated in the absence of the intervention would be

$$\widehat{Y}^N_{1t} = \sum_{j=2}^{J} \widehat{w}_j Y_{jt}, \tag{1.14}$$

where the $(J \times 1)$ vector of weights $\widehat{W} = (\widehat{w}_2, \ldots, \widehat{w}_J)'$ is chosen to minimize the distance between the treated and the other units in pre-intervention characteristics (see Section 1.1).

Then, the effect on the main treated would be estimated as

$$\widehat{\theta}_{1t} = Y_{1t} - \sum_{j=2}^{J} \widehat{w}_j Y_{jt}. \tag{1.15}$$

As units 2 to m are potentially affected by the intervention, their post-intervention outcomes are given by

$$Y_{jt} = Y^N_{jt} + \gamma_{jt}, \; j = 2, \ldots, m. \tag{1.16}$$

Our first assumption is that if units 2 to m were not affected by the intervention, the standard SMC would work, formally

Assumption 1: There exists a set of weights $W^* = (w^*_2, ..., w^*_J)'$ such that $Y^N_{1t} = \sum_{j=2}^{J} w^*_j Y^N_{jt}$.

In other words, Assumption 1 assumes that the only violation of the standard SCM assumptions is the presence of post intervention effects. Notice that as we discuss in more details in Section 1.3.2 in many application Assumption 1 might not be satisfied exactly but only approximately, this would have the same consequences on our iSCM as it would on a standard SCM.

Lemma 1: Under Assumption 1 as $T_0 \to \infty$

$$\widehat{\theta}_{1t} \to \theta_{1t} - \sum_{j=2}^{m} \widehat{w}_j \gamma_{jt} \tag{1.17}$$

Proof of Lemma 1: Under Assumption 1 and using the observational rule and the results of Abadie et al. 2010 as $T_0 \to \infty$ we have

$$\begin{aligned}
\widehat{Y}_{1t}^N &= \sum_{j=2}^{J} \widehat{w}_j Y_{jt} \\
&= \sum_{j=m+1}^{J} \widehat{w}_j Y_{jt}^N + \sum_{j=2}^{m} \widehat{w}_j \left(Y_{jt}^N + \gamma_{jt} \right) \\
&= \sum_{j=2}^{J} \widehat{w}_j Y_{jt}^N + \sum_{j=2}^{m} \widehat{w}_j \gamma_{jt} \\
&\to Y_{1t}^N + \sum_{j=2}^{m} \widehat{w}_j \gamma_{jt}
\end{aligned}$$

This immediately implies that

$$\widehat{\theta}_{1t} \to \theta_{1t} - \sum_{j=2}^{m} \widehat{w}_j \gamma_{jt}.$$

□

Lemma 1 shows how the presence of post interventions effects affects the standard SCM under assumption 1.

Remark: It is important to notice that for each unit $j = 2, \ldots, m$ if either γ_{jt} or $\widehat{w}_j$ is zero that unit does not induce 'bias' in $\widehat{\theta}_{1t}$. This implies that units that receive a low estimated weight need to have an extremely large effect to induce non negligible bias in $\widehat{\theta}_{1t}$. For this reason, units that receive a low weight can be relatively safely treated as pure controls when estimating θ_{1t} in empirical applications.

Consider a generic potentially affected unit i , $i \in [2, \ldots, m]$. Let $\widehat{L}^i$ the weight obtained using a standard SCM, including the main treated (unit 1) and the other $m-1$ potentially affected units in the donor pool, to estimate Y_{it}^N, and let

$$\widehat{Y}_{it}^N = \sum_{j \neq i} \widehat{l}_j^i Y_{jt}, \tag{1.18}$$

be the resulting SC estimator.

Let $\mathcal{J} = \{1, ..., J\}$, we assume that for units 2 to m without the effect of the intervention on the main treated and the other potentially affected units, the standard SCM would work, formally

Assumption 2: There exists a set of weights l_j^{i*}, $j \in \mathcal{J} \backslash \{i\}$, such that $Y_{it}^N = \sum_{j \in \mathcal{J} \backslash \{i\}} l_j^{i*} Y_{jt}^N$, $\forall\, i = 2, \ldots, m$.

In many applications also Assumption 2 might not be satisfied exactly but only approximately. We refer to Section 1.3.2 to a deeper discussion on this but intuitively as soon as the approximation is good enough this should only induce negligible bias as in the standard SCM case.

Lemma 2: Under Assumption 2 as $T_0 \to \infty$

$$\widehat{\gamma}_{it} \to \gamma_{it} - \sum_{j \in M \backslash \{i\}} \widehat{l}_j^i \gamma_{jt} - \widehat{l}_1^i \theta_{1t}. \tag{1.19}$$

Proof of Lemma 2: Under Assumption 2, using the observational rule and the results of Abadie et al. 2010 as $T_0 \to \infty$ we have

$$\widehat{Y}_{it}^N \to Y_{it}^N + \sum_{j \in M \backslash \{i\}} \widehat{l}_j^i \gamma_{jt} + \widehat{l}_1^i \theta_{1t}, \tag{1.20}$$

with $M = \{2, ..., m\}$. It follows

$$\widehat{\gamma}_{it} \to \gamma_{it} - \sum_{j \in M \backslash \{i\}} \widehat{l}_j^i \gamma_{jt} - \widehat{l}_1^i \theta_{1t}.$$

□

When Assumption 1 and 2 hold exactly simultaneous, theoretically, it is possible to exclude potentially affected units and only include pure controls units in the donor pool. However, in practice as we graphically show in Section 1.3.2 only using pure controls units it is very likely to increase the risk of interpolation bias, as it makes it more likely that units that are very different from the treated receive substantial weights.

When, as it is often the case in the empirical applications, Assumptions 1 and 2 only approximately hold as the potentially affected units are usually the closest to the treated unit (also because they are the ones that receive the highest weights), using iSCM it is very likely to provide a much better approximation than a restricted version that exclude the potentially affected units as we illustrate in Figure 1.2.

Combining the results of Lemma 1 and Lemma 2, as $T_0 \to \infty$ the following system of equations holds

$$
\begin{aligned}
\widehat{\theta}_{1t} &= \theta_{1t} - \sum_{j \in M} \widehat{w}_j \gamma_{jt} \\
\widehat{\gamma}_{2t} &= \gamma_{2t} - \sum_{j \in M \setminus \{2\}} \widehat{l}_j^2 \gamma_{jt} - \widehat{l}_1^2 \theta_{1t} \\
\widehat{\gamma}_{3t} &= \gamma_{3t} - \sum_{j \in M \setminus \{3\}} \widehat{l}_j^3 \gamma_{jt} - \widehat{l}_1^3 \theta_{1t} \\
&\dots \\
\widehat{\gamma}_{mt} &= \gamma_{jt} - \sum_{j \in M \setminus \{m\}} \widehat{l}_j^m \gamma_{jt} - \widehat{l}_1^m \theta_{1t}
\end{aligned}
$$

After some simple manipulations we obtain:

$$
\begin{aligned}
\widehat{\theta}_{1t} &= \theta_{1t} - \widehat{w}_2 \gamma_{2t} - \widehat{w}_3 \gamma_{3t} - \dots - \widehat{w}_m \gamma_{mt} \\
\widehat{\gamma}_{2t} &= -\widehat{l}_1^2 \theta_{1t} + \gamma_{2t} - \widehat{l}_3^2 \gamma_{3t} - \dots - \widehat{l}_m^2 \gamma_{mt} \\
\widehat{\gamma}_{3t} &= -\widehat{l}_1^3 \theta_{1t} - \widehat{l}_2^3 \gamma_{2t} + \gamma_{3t} - \dots - \widehat{l}_m^3 \gamma_{mt} \\
&\dots \\
\widehat{\gamma}_{mt} &= -\widehat{l}_1^m \theta_{1t} - \widehat{l}_2^m \gamma_{2t} - \widehat{l}_3^m \gamma_{3t} - \dots + \gamma_{mt}
\end{aligned}
$$

This is a system of m equations with m unknowns, i.e., the treatment effect on the main treated and the $m-1$ effects on the potentially affected units.

We can write this system in matrix form, denoting by ϑ_t the $(m \times 1)$ vector of unknown parameters (our effects of interest), by $\widehat{\Omega}$ the $(m \times m)$ matrix of known quantities (our estimated weights) that has ones on the main diagonal and by β_t the $(m \times 1)$ vector of known quantities (biased estimated effects), as

$$\widehat{\beta}_t = \begin{pmatrix} \widehat{\theta}_{1t} \\ \widehat{\gamma}_{2t} \\ \widehat{\gamma}_{3t} \\ \vdots \\ \widehat{\gamma}_{mt} \end{pmatrix} \qquad \widehat{\Omega} = \begin{pmatrix} 1 & -\widehat{w}_2 & -\widehat{w}_3 & \dots & -\widehat{w}_m \\ -\widehat{l}_1^2 & 1 & -\widehat{l}_3^2 & \dots & -\widehat{l}_m^2 \\ -\widehat{l}_1^3 & -\widehat{l}_2^3 & 1 & \dots & -\widehat{l}_m^3 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ -\widehat{l}_1^m & -\widehat{l}_2^m & -\widehat{l}_3^m & \dots & 1 \end{pmatrix} \qquad \vartheta_t = \begin{pmatrix} \theta_{1t} \\ \gamma_{2t} \\ \gamma_{3t} \\ \vdots \\ \gamma_{mt} \end{pmatrix} \tag{1.21}$$

We now assume that $\widehat{\Omega}$ is invertible, namely

Assumption 3: $\widehat{\Omega}$ is non-singular.

It is easy to show that $\widehat{\Omega}$ is always invertible, if $m \leq J - 1$, except for the extreme cases where two units give weight 1 to each other and/or every single weight associated with the pure control units is zero (see Appendix A.1).

We now state our main result in the following theorem.

Theorem 1: Under Assumption 3, we have

$$\widehat{\vartheta}_t^{iSCM} = \widehat{\Omega}^{-1}\widehat{\beta}_t \to \vartheta_t.$$

Proof of Theorem 1: The result immediately follows from equation 1.21 using the fact that $\widehat{\Omega}$ is invertible. $\square$

The result in Theorem 1 can be readily used to identify our effects of interest by simply applying Cramer's rule:

$$\widehat{\vartheta}_{jt}^{iSCM} = \frac{\det(\widehat{\Omega}_{j,t})}{\det(\widehat{\Omega})} \qquad j = 1, ..., m.$$

where $\widehat{\Omega}_{j,t}$ is the matrix obtained by replacing the j-th column of $\widehat{\Omega}$ by the vector $\widehat{\beta}_t$.

The expression above makes it very easy to construct estimators of our parameters of interest that only require very basic linear algebra operations together with any SCM-type estimator for the weight matrix $\widehat{\Omega}$ and the vector $\widehat{\beta}_t$.

1.3.2 Why use iSCM?

In the SCM, the credibility of estimates depends on the capacity to reproduce the counterfactual. It is therefore advisable to include in the donor pool units affected by the same characteristics and regional shocks as the treated unit to recover the counterfactual. Often, these units are either directly or indirectly affected by the intervention, e.g., others treated units or units potentially affected by spillover effects are likely to be the the closest (geographically and economically) to the main treated unit. For example Abadie, 2021 propose to include units potentially affected by spillover in the donor pool especially if the researcher has a prior regarding the potential direction of the bias. Nevertheless, if the spillover effects are large, the standard SC estimator might have a large bias. However, discarding those could substantially decrease the quality of the match between the characteristics of the treated and synthetic control as those units are typically the closest to the treated. There seems to be a trade-off between using the 'right' donor pool and and the bias induced by spillover effects (Abadie 2021). Our iSCM, allows to safely include the potentially affected units in the donor pool and potentially reduce interpolation bias.

More formally, even though SCM is based on the assumption of a perfect pre-treatment fit ($X_1 - X_0W = 0$), Abadie et al. 2010 argues that, in practice, in most empirical applications, this condition is likely violated. We can replace this assumption with the weaker assumption that a linear combination of the control units can only approximate the pre-treatment characteristics of the treated, i.e., $X_1 - X_0W \approx 0$ (Abadie 2021). In particular, X_1 would be equal to X_0W if unit 1 falls inside the convex hull or can only approximate X_0W if it falls outside but close.

In the former case, the weights that minimize equation 1.2 may not be unique, so there might exist infinite solutions such that $X_1 = X_0W$. This means that units that are far away from the treated might receive substantial weights [3]

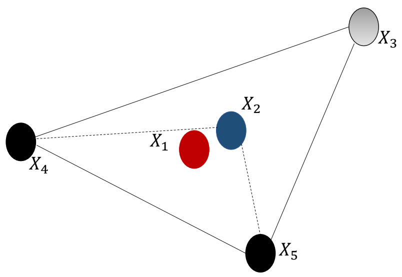
[3]Abadie and L'Hour, 2019 propose a solution to penalize the X_j that differs from the X_1.

with the risk of overfitting.
In the latter case, the solution to the minimization problem is unique and sparse[4] because the synthetic control X_0W is a projection of X_1 on the convex hull of X_0. As discussed by Abadie, 2021, it is common that in empirical applications X_1 does not belong to the convex hull of the control group. If X_1 falls far from the convex hull, Abadie et al., 2010 suggest avoiding using the SCM. On the other hand, if X_1 falls outside but close to the convex hull, the SCM can be used but paying attention to the units included in the donor pool. In this case, it is very likely that including affected units is the preferable choice.
In Figures 1.1 and 1.2, we graphically represent possible scenarios from the point of view of unit 1, on the left side, and unit 2, on the right side. We assume that X_1, i.e., the red point, is the vector that includes the pre-intervention predictors of the main treated, X_2, i.e., the blue point, is the vector that includes the pre-intervention predictors of the only affected unit. All other points represent pure control units, when marked in black they contribute to the synthetic control while when marked in grey they do not contribute.

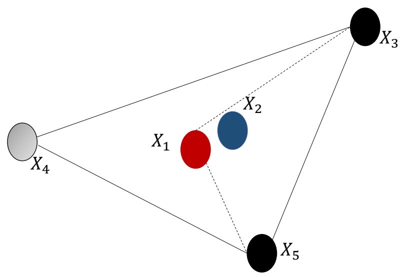
Figure 1.1 shows the scenarios in which *the main treated and the affected unit lie inside the convex hull*. In these cases, the algorithm may select a solution that perfectly reproduce X_1 only using pure controls. Nevertheless, as shown in Panel 1.1a (that describes the scenarios for unit X_1) including the affected unit could allow excluding the farthest pure control unit X_3, restricting the donor pool and avoiding interpolation bias that may be unchecked under the illusion of perfect fit (see Abadie 2021). This is also true even when the main treated and affected unit are farther, as in Panel 1.1c. The same goes for the affected unit X_2. Including the main treated X_1 in the donor pool, could allow excluding X_4, as shown in Panels 1.1b and 1.1d.

Figure 1.2 shows the scenarios in which *only one between the main treated and the affected unit lies inside the convex hull*.
Panel 1.2a shows the case in which *the main treated lies outside but close to the convex hull*. Both excluding and including the affected unit we can only have $X_1 \approx X_0W$ but excluding the affected units leads to a bigger discrepancy between $X_1 - X_0W$, therefore it is better to include it in the donor pool. Panel

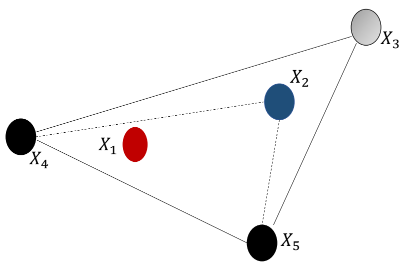
[4]The uniqueness and sparsity of the matrix favor the interpretability of the results.



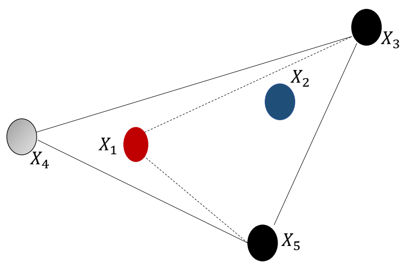
(A) Main treated convex hull



(B) Affected unit convex hull



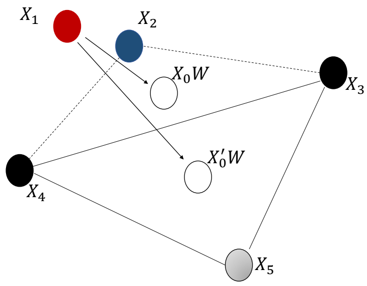
(C) Main treated convex hull



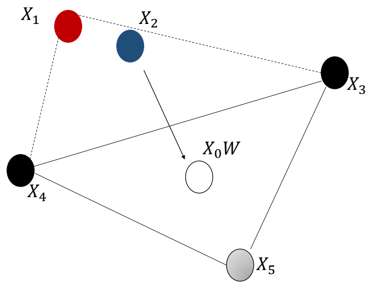
(D) Affected unit convex hull

FIGURE 1.1: The main treated and the affected unit lie inside the convex hull

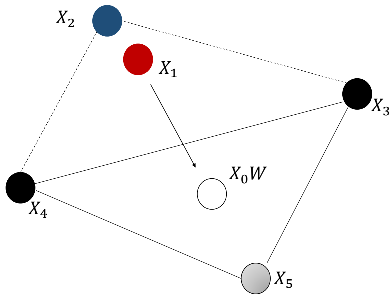
1.2b shows the same situation of 1.2a but from the point of view of X_2, i.e., *the affected unit lies outside the convex hull if the main treated is ruled out*. It is therefore advisable to include the main treated.
Panel 1.2c shows the case in which *the main treated lies inside the convex hull only if we include the affected unit in the control group*. Moreover, including it could likely reduce the convex hull, avoiding the possibility of considering units farther from the main treated, as the X_5. Panel 1.2d shows the same situation of 1.2c but the point of view of X_2, i.e., the case in which *the affected unit lies outside but close to the convex hull*. Both excluding and including the main treated only allows $X_2 \approx X_0 W$ but excluding X_1 leads to a bigger discrepancy between $X_2 - X_0 W$.
Panel 1.2e shows the case in which both including and excluding the affected unit, *the main treated lies outside the convex hull* in any case. Nevertheless, including X_2 could rule out the X_5, the unit with the farthest pre-treatment characteristics to the main treated. Panel 1.2f shows the same situation as 1.2e but the point of view of X_2, i.e., both including and excluding the main treated, *the affected unit lies inside the convex hull* in any case. It is likely that including the main treated could avoid including the farthest unit for the affected unit, X_3.
Panel 1.2g shows the case in which *the main treated lies inside the convex hull and the affected unit outside and far*. This case can be ruled out by the fact that affected unit is not likely to receive substantial weight. Panel 1.2h shows the same situation of 1.2g but from the point of view of X_2, i.e., both including and excluding the main treated, *affected unit lies outside the convex hull* in any case. However, including the main treated could rule out the farthest unit for the affected unit X_4.



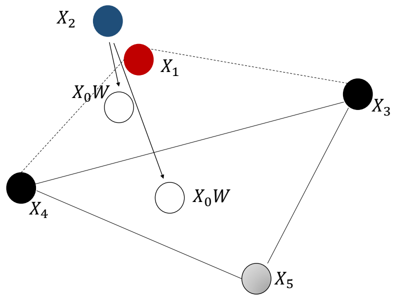
(A) Main treated convex hull



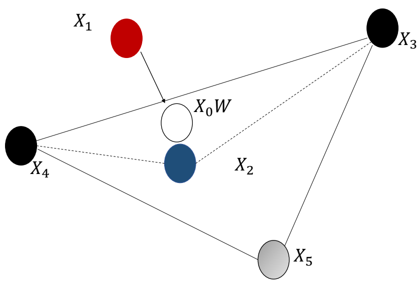
(B) Affected unit convex hull



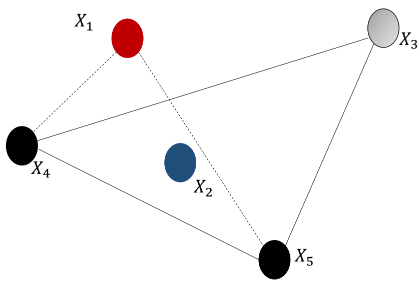
(C) Main treated convex hull



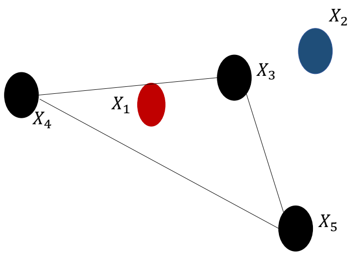
(D) Affected unit convex hull



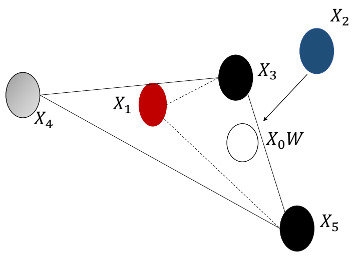
(E) Main treated convex hull



(F) Affected unit convex hull



(G) Main treated convex hull



(H) Affected unit convex hull

FIGURE 1.2: Only one between the main treated and the affected unit lies inside the convex hull

1.3.3 Implementation

Before implementing our iSCM we advice to follow the following steps to judge the potential gain over running a 'restricted' SCM where potentially affected units are not included in the donor pool.

1. Implement SCM including units potentially affected by the intervention (i.e., other treated units or units affected by spillovers).

- If the potentially affected units receive low or zero weights, they induce a negligible bias and can be used as pure controls.
- If the potentially affected units receive high weights, we can proceed with step 2.

2. Implement the 'restricted' SCM, i.e., excluding units potentially affected by the intervention and:

   (a) Compare the bias in term of predictors $(X_1 - X_0\widehat{W})$ between 'restricted' SCM and the standard SCM;

   (b) Compare Root Mean Squared Prediction Error (RMSPE) in the pre intervention period of the 'restricted' SCM and standard SCM.

$$RMSPE = \left(\frac{1}{T_0} \sum_{t=1}^{T_0} (Y_{1t} - \sum_{j \neq 1} \widehat{w}_j Y_{jt})^2 \right)^{1/2}.$$

   between restricted SCM and the standard SCM.

- If $(X_1 - X_0^{res}\widehat{W}^{res}) < (X_1 - X_0\widehat{W})$ and $RMSPE^{res} < RMSPE$, it could be more convenient proceed with the 'restricted' SCM.
- If $(X_1 - X_0^{res}\widehat{W}^{res}) > (X_1 - X_0\widehat{W})$ and/or $RMSPE^{res} > RMSPE$, we advice to use iSCM.

Repeat this steps considering every potentially affected unit as if it was the main treated. In case there is no substantial gain of including the treated in the donor pool of the potentially affected units our iSCM simplifies as shown in the Equation 1.29 below for a special case.

To further illustrate our results, it is useful to consider the special case where, together with the main treated unit, only one additional unit is potentially affected by the intervention ($m = 1$)[5].

First, we show the standard case in which *each unit needs to be included in the donor pool of the other* and then the simplified case in which *the affected unit needs to be included in the donor pool of the main treated but not vice-versa*.

- **Each unit needs to be included in the donor pool of the other**

  In this case, we have a simple system of equations for each post-treatment period, as described in Lemma 1 and Lemma 2:

$$\begin{cases} \widehat{\theta}_t = \theta_t - \widehat{w}_2 \gamma_t \\ \widehat{\gamma}_t = -\widehat{l}_1 \theta_t + \gamma_t \end{cases} \tag{1.22}$$

  where ($\widehat{\theta}_t$) is the estimated effect for the main treated; ($\widehat{\gamma}_t$) is the estimated effect for the potentially affected unit; ($\widehat{w}_2$) and ($\widehat{l}_1$) are the estimated weights; (θ_t and γ_t) are the the unknowns effects.

  Therefore, we have

$$\widehat{\beta}_t = \begin{pmatrix} \widehat{\theta}_t \\ \widehat{\gamma}_t \end{pmatrix}, \qquad \widehat{\Omega} = \begin{pmatrix} 1 & -\widehat{w}_2 \\ -\widehat{l}_1 & 1 \end{pmatrix}, \qquad \vartheta_t = \begin{pmatrix} \theta_t \\ \gamma_t \end{pmatrix}. \tag{1.23}$$

  To derive expressions for our parameters of interest we need to find $\det(\widehat{\Omega})$, $\det(\widehat{\Omega}_{1,t})$ and $\det(\widehat{\Omega}_{2,t})$, which are given by

$$\det(\widehat{\Omega}) = \begin{vmatrix} 1 & -\widehat{w}_2 \\ -\widehat{l}_1 & 1 \end{vmatrix} = 1 - \widehat{w}_2 \widehat{l}_1, \tag{1.24}$$

$$\det(\widehat{\Omega}_{1,t}) = \begin{vmatrix} \widehat{\theta}_t & -\widehat{w}_2 \\ \widehat{\gamma}_t & 1 \end{vmatrix} = \widehat{\theta}_t + \widehat{w}_2 \widehat{\gamma}_t, \tag{1.25}$$

[5] In AppendixA.2, we show the case with two additional units potentially affected.

$$\det(\widehat{\Omega}_{2,t}) = \begin{vmatrix} 1 & \widehat{\theta}_t \\ -\widehat{l}_1 & \widehat{\gamma}_t \end{vmatrix} = \widehat{\gamma}_t + \widehat{l}_1\widehat{\theta}_t. \tag{1.26}$$

Following Cramer's rule, we obtain

$$\widehat{\theta}_t^{iSCM} = \frac{\widehat{\theta}_t + \widehat{w}_2\widehat{\gamma}_t}{1 - \widehat{w}_2\widehat{l}_1} \tag{1.27}$$

$$\widehat{\gamma}_t^{iSCM} = \frac{\widehat{\gamma}_t + \widehat{l}_1\widehat{\theta}_t}{1 - \widehat{w}_2\widehat{l}_1} \tag{1.28}$$

In this case, it is easy to see that $\det(\widehat{\Omega})$ is always different from zero, except if $\widehat{w}_2 = \widehat{l}_1 = 1$. Thus, our parameters of interest are always identified unless the main treated gives weight 1 to the other affected unit, which in turn gives weight 1 to the main treated. This would be the case, for example, if there are no pure control units.

- **The affected unit needs to be included in the donor pool of the main treated but not vice-versa**

  When the main treated does not enter the donor pool of the affected unit the system further simplifies to

$$\begin{cases} \widehat{\theta}_t = \theta_t - \widehat{w}_2\gamma_t \\ \widehat{\gamma}_t = \gamma_t. \end{cases} \tag{1.29}$$

  Thus, in order to find the unbiased effect θ_t is sufficient to add the effect of the potentially affected unit γ_t multiplied for the estimated weight assigned to it $\widehat{w}_2$ from the estimated effect for the main treated $\widehat{\theta}_t$.

1.3.4 Inference

Dealing with only a few units makes inference for synthetic control-based methods, like ours, complicated. We can, however, easily adapt existing methods to our setting. The most popular choice is to implement permutation tests Abadie et al., 2010 and Abadie et al., 2015 propose placebo tests in time, i.e., reassigning the intervention artificially before its real implementation and placebo tests in space, i.e., reassigning the intervention artificially for units in the control group. The latter approach is often preferred because of possible shocks that might have occurred in the past affecting units differently. In space placebo tests measure the statistical significance of the effect through the ratio between the root mean squared prediction errors (RMSPE) in the post-treatment period and in the pre-treatment period. The RMSPE measures the lack of fit between the observed outcome and its synthetic control. In our framework the presence of units affected by intervention in the donor pool, requires a small modification in the way we compute the post-intervention RMSPE. We suggest computing the post-intervention RMSPE by first subtracting from the outcomes of each affected unit, except the one for which we are implementing the inference procedure, the respective effect estimated with iSCM.
For the main treated unit the modified RMSPE ratio becomes

$$r_1 = \frac{\left(\frac{1}{T-T_0}\sum_{t=T_0+1}^{T}(Y_{1t} - (\widehat{Y}_{1t}^N - \sum_{j=2}^{m}\widehat{w}_j\widehat{\gamma}_{jt}^{iSCM}))^2\right)^{1/2}}{\left(\frac{1}{T_0}\sum_{t=1}^{T_0}(Y_{1t} - \widehat{Y}_{1t}^N)^2\right)^{1/2}},$$

while for the potentially affected units we have

$$r_i = \frac{\left(\frac{1}{T-T_0}\sum_{t=T_0+1}^{T}(Y_{it} - (\widehat{Y}_{it}^N - \sum_{i\in M\setminus\{i\}}\widehat{l}_i^i\widehat{\gamma}_{it}^{iSCM} - \widehat{\gamma}_{it}^{iSCM}))^2\right)^{1/2}}{\left(\frac{1}{T_0}\sum_{t=1}^{T_0}(Y_{it} - \widehat{Y}_{it}^N)^2\right)^{1/2}}, i = 2, \ldots, M.$$

Finally, for the pure control units we have

$$r_j = \frac{\left(\frac{1}{T-T_0}\sum_{t=T_0+1}^{T}(Y_{jt} - (\widehat{Y}_{jt}^N - \sum_{i\in M}\widehat{h}_j\widehat{\gamma}_{jt}^{iSCM}))^2\right)^{1/2}}{\left(\frac{1}{T_0}\sum_{t=1}^{T_0}(Y_{jt} - \widehat{Y}_{jt}^N)^2\right)^{1/2}}, j = M+1,\dots,J,$$

where h are the corresponding synthetic control weights.

This idea can be easily applied to other inference procedures available in the literature.
For example, Firpo and Possebom, 2018 construct p-values extending the previous procedure and running a sensitivity analysis. The Abadie et al., 2015 benchmark imposes a restrictive choice on weights, while the Firpo and Possebom's extesion does not. Their sensitivity analysis procedure consider the weights of each placebo treatment assignment, given a sensitivity parameter, using these ones to run the permutation test's p-value. If the hypothesis of no effect is rejected, they measure the robustness changing the sensitivity parameter. Inference procedure related to Andrew's P test are developed by Cao and Dowd, 2019 and Chernozhukov et al., 2020, based on sharp null hypotheses and permutation distributions, even if Andrews, 2003 assume correct specification while Chernozhukov et al., 2020 admits misspecification. Cattaneo et al., 2019 build predictive interval to give a natural quantification of uncertainty Li, 2019, uses projection theory and asymptotic distribution.

1.4 Conclusion

We introduce iSCM, a modification of the standard SCM, that allows including units potentially affected by an intervention in the donor pool. Our method is useful in applications where it is either important to include other treated units in the donor pool or where some of units are affected indirectly by the intervention (spillover effects).
The iSCM requires that the standard SCM would be valid in the absence of post-intervention effects as well as the presence of at least one pure control unit in the donor pool. A big advantage of iSCM is that it can be easily implemented using the standard synthetic control algorithm or any new estimation method available in the literature.

Chapter 2

The economic impact of the German reunification

In this chapter, we use iSCM to re-estimate the effect of German reunification on West Germany's per capita GDP, revisiting an empirical study conducted by Abadie et al., 2015 and Abadie, 2021. As the authors point out, it is possible that German reunification had spillover effects on a neighboring country like Austria, which plays an important role in constructing synthetic West Germany; such a spillover effect, if large, would introduce a large bias. Moreover, for the same reason, excluding it from the donor pool is likely to reduce the quality of the match between treated and synthetic units.

2.1 An overview

At the end of the eighties, the process of internal dissolution within USSR began and its leader, Gorbachev, proposed some liberal reforms. Honecker, the East Germany head of State, disagreed by these to the point of to forbid circulation of Soviet publications, viewed as dangerously subversive. On the other hand, the Hungarian government opened borders with Austria. This allowed East Germans to reach West Germany through Hungary, Czechoslovakia, and Poland. To halt the political embarrassment due to the massive influx of refugees trying to escape from East German, a mistake was made. On November 9, a communist functionary announced at a televised news conference the permission to pass to West Germany, without limitation, and to immediate effect. The real meaning of the message wanted to indicate the possibility of requesting exit visas during normal working hours. In reality,

people interpreted this as a decision to open the frontiers. The same evening tens of thousands of East Germans demanded the guards let them pass the Wall. These guards, taken aback, let them go through. It started a process that gave East German people a voice: free elections culminated in March 1990 with the fall of the Party of Democratic Socialism and a government victory allied with the then-Chancellor Kohl. And so, began negotiations for the reunification treaty. In July, a monetary union gave East Germany the currency of the West. In September, the treaty was ratified, and on October 3, 1990, after 45 years, the German Democratic Republic ('East Germany') and the Federal Republic of Germany ('West Germany') were officially reunified. One of the most important events that changed the history of the last 30 years entailed a complicated process of making two radically different countries into one. Integrating a socialist into a capitalist system consists of a series of difficulties. The costs of reunification were social and economic. The economic gap between the two Germanys represented the greatest difficulty because the differences in the two economies were considerable. In 1989, the GDP per capita of West Germany was about three times higher than that of East Germany (Schinasi et al. 1990).
As mentioned by Abadie et al., 2015, many studies have focused on the consequences of the reunification for East Germany and the convergence, ignoring the economic consequences for West Germany. Nevertheless, bringing East Germany to the level of Western democracy would have huge costs, which would have meant less money for everyone. The State of Eastern German economy was hard to manage and worse than anyone had realized: few firms could compete on the world market, and the infrastructure required massive capital investment to provide the basis for future economic growth. For this reason, Abadie et al., 2015 focus on the economic impact for West Germany, finding significant negative effects on West Germany's GDP per capita starting from 1992 onward.

Defined as one of the most important historical milestones of European history after 1945, German reunification most likely affected not only the German economy but also other countries. In particular, Austria has had close links with Germany historically because the two countries share the same language and, to a great extent, a common history. In 1938, Austria was

annexed by the Third Reich that benefited from its raw materials and labor to complete the German rearmament. In 1945, Austria was separated from Germany. However, the economic cooperation between Austria and West Germany continued during the Cold War.
Hence, German reunification could have had negative spillover effects on Austria's economic growth because West Germany diverted demand and investment from Austria to East Germany.
Moreover, Austria had an economic link with East Germany. In 1980s, they were economic partners. Since 20 percent of East Germany's national debt was due to Austrian loans, so much so the role of Austria was decisive when, in 1982, East Germany risked bankruptcy. The economic relationship dwindled in the mid-1980s but recovered when Austria provided vast amounts of electricity to East Germany, and consumer goods for about a billion Austrian shillings, because of communal elections, at the end of the decade (Gehler and Graf 2018). This tight partnership was likely affected by German reunification: Austria's role in supporting East Germany is failing, involving a negative spillover.

2.2 Data and empirical identification strategy

Abadie et al., 2015 conduct an empirical study to estimate the economic impact of German Reunification for West Germany, applying the SCM. They use a panel data of 16 OECD countries observed for a period 1960-2003 to provide a synthetic West Germany, i.e., a comparison unit given by a weighted average of OECD countries that best resembles the predictors of economic growth of West Germany in the period before 1990. Synthetic West Germany is composed of Austria (42%), United States (22%), Japan (16%), Switzerland (11%), and the Netherlands (9%). The results, i.e., the difference between the GDP per capita observed for West Germany from 1990 to 2003 and synthetic West Germany suggest that German reunification had a negative impact on West German income.
As the authors point out, it is possible that German reunification had spillover effects on a neighboring country like Austria[1]. This would imply that the big negative effect they found is likely to be an upper bound of the true effect.

[1]Given that other European countries receive low weights, the impact of potential spillover effects on those countries would arguable be negligible as shown by Lemma 1 in

Our iSCM is an attractive method for this application. We start by implementing the procedure 1.3.3, as described in the previous chapter, to see if we can improve over discarding Austria from the donor pool.
Given the high weight (42%) that West Germany assigns to Austria, step 1 suggests us to go to step 2, i.e., to implement the SCM excluding Austria from the donor pool and:

1. Compare the discrepancies in the observed characteristics between the treated and synthetic control ($X_1 - X_0W$) when using the 'restricted' and standard SCM.

2. Compare the RMSPE in the pre-treatment period of the 'restricted' and standard SCM.

We use country-level panel data covering the period 1960-2003, with the post-intervention period starting in 1990. Except for Austria, the pure control countries in the donor pool include 15 other OECD countries: Australia, Belgium, Denmark, France, Greece, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Spain, Switzerland, the United Kingdom, and the United States.
The outcome variable is the real per capita GDP at Purchasing Power Parity (PPP) measured in 2002 USD. The set pre-intervention covariates, i.e., the predictors of economic growth, includes: per capita GDP, inflation rate (annual percentage change in consumer price, based on 1995), industry share of value added, investment rate (ratio of real domestic private plus public investment to real GDP), schooling (percentage of secondary school attained in the total population aged 25 and older), and a measure of trade openness (export plus imports as a percentage of GDP).
To estimate the economic effect on West Germany excluding Austria from the donor pool, the so-called 'restricted' version, we use the same specification as in Abadie et al., 2015. Particularly, in order to find the weights to assign to each covariate, we split the pre-treatment period into a training period (1971–80) and a validation period (1981–90). The weights are then selected by minimizing the out-of-sample error in the validation period.
Table 2.1 shows the pre-intervention characteristics for West Germany (first

the previous chapter. However, in section 2.4.3, we report the case of spillover affecting the European countries receiving positive weights.

column), synthetic inclusive West Germany (second column), 'restricted' synthetic West Germany (third column), the bias, i.e., the differences in absolute terms between the predictors' values for West Germany and synthetic West Germany (fourth column), and 'restricted' synthetic West Germany (fifth column). It suggests that the synthetic version of West Germany closely reproduces West Germany respect to the 'restricted' version. The standard synthetic is closer to West Germany than the 'restricted' synthetic.

TABLE 2.1: Economic growth predictors before German Reunification: synthetic West Germany and 'restricted' synthetic West Germany

	West Germany	Synthetic West Germany	'Restricted' Synthetic West Germany	Bias	'Restricted' Bias
GDP per capita	15,808.90	15,804.64	16,138.83	4.26	329.93
Trade openness	56.78	56.91	50.73	0.14	6.04
Inflation rate	2.60	3.51	3.38	0.91	0.79
Industry share	34.54	34.38	33.30	0.15	1.24
Schooling	55.50	55.23	50.71	0.27	4.79
Investment rate	27.02	27.04	25.70	0.02	1.31

Then, we look at the RMSPE in the pre-treatment, which gives us a measure of the lack of fit. The pre-treatment RMSPE for the 'restricted' version (270.74) is bigger than the pre-treatment RMSPE for the inclusive version (119.07). The inclusive synthetic version of West Germany in the pre-reunification period reproduces almost perfectly West Germany's per capita GDP. Excluding Austria substantially deteriorates the pre-reunification fit.

We repeat now the same procedure 1.3.3 for Austria.
The first step is to implement the standard SCM on Austria, including West Germany in Austria's donor pool. This allows us to judge whether Austria gives enough weight to West Germany to have a large bias in estimating the spillover effect.
We use a slightly different specification than the one used for West Germany to estimate the weights. As described in Gehler and Graf, 2018, in 1980, right

before the sample split cut-off, Austria provided several loans to East Germany, and in return, its nationalized industries received large-scale orders. This most likely fostered Austrian exports and contributed to job creation in its industries. Thus, the sample split might catch the effect of this economic shock. This is corroborated by the fact that using the same specification as in Abadie et al., 2015 also for Austria leads to a bad pre-treatment fit. For this reason, we decided to follow Abadie et al., 2010 in choosing the covariates weights for synthetic Austria, which are selected such that the mean squared prediction error of the outcome variable is minimized for the entire pre-treatment period.

Table 2.2 shows the estimated synthetic weights for Austria in the third column. Synthetic Austria is a combination of West Germany (33%), the Netherlands (31%), Japan (21%), Belgium (12%), and Norway (3%). So, Austria gives the highest weight to West Germany and allows to proceed with step 2.

TABLE 2.2: Synthetic control weights for West Germany and Austria

Country	Synthetic West Germany Weights	Synthetic Austria Weights
West Germany	-	0.33
Austria	0.42	-
Australia	0	0
Belgium	0	0.12
Denmark	0	0
France	0	0
Greece	0	0
Italy	0	0
Japan	0.16	0.21
Netherlands	0.09	0.31
New Zealand	0	0
Norway	0	0.03
Portugal	0	0
Spain	0	0
Switzerland	0.11	0
UK	0	0
USA	0.22	0

The second step consists of comparing bias in pre-intervention predictors between treated and synthetic and the RMSPE both for standard and for 'restricted' SCM versions.

Table 2.3 shows the pre-intervention characteristics for Austria (first column), inclusive synthetic Austria (second column), and 'restricted' synthetic Austria (third column), the bias, i.e., the differences in absolute terms between the predictors' values for Austria and synthetic Austria (fourth column), and 'restricted' synthetic Austria (fifth column). It suggests that the standard version is a little better at reproducing Austria in pre-treatment predictors than the 'restricted' version, except for the GDP per capita mean. Nevertheless, the pre-intervention RMSPE for the 'restricted' version (181.22) is slightly lower than the pre-intervention RMSPE for the inclusive version (194.67).

As the discrepancy in the predictors is much worse when using the 'restricted' SCM and the increase in the RMSPE is small we decided to include West Germany in Austria's donor pool. In Appendix B.1, we propose the version in which West Germany is excluded from Austria's donor pool. Excluding West Germany, the effect is slightly positive, which is rather unlikely, confirming the importance of including it in the donor pool.

TABLE 2.3: Economic growth predictors before German Reunification: synthetic Austria and 'restricted' synthetic Austria

	Austria	Synthetic Austria	'Restricted' Synthetic Austria	Bias	'Restricted' Bias
GDP per capita	10781.80	10798.41	10778.61	16.61	3.19
Trade openness	69.45	69.43	83.13	0.02	13.68
Inflation rate	4.91	4.92	5.59	0.01	0.68
Industry share	37.81	37.81	37.58	0.00	0.23
Schooling	53.25	45.71	35.44	7.54	17.81
Investment rate	26.64	26.64	27.03	0.00	0.38

2.3 Implementation

Now we can safely apply iSCM, as follows:

1. After constructing Synthetic West Germany including Austria in the donor pool, estimate the bias treatment effect for West Germany $\widehat{\theta}_t$ and the weight assigned to Austria $\hat{w}_A$.
2. After constructing Synthetic Austria including West Germany in the donor pool, estimate the bias spillover effect $\widehat{\gamma}_t$ and the weight assigned to West Germany $\hat{l}_{WG}$.
3. Estimate the unbiased treatment effect on West Germany as $\frac{\widehat{\theta}_t+\hat{w}_A\widehat{\gamma}_t}{1-\hat{w}_A\hat{l}_{WG}}$.
4. Estimate the unbiased spillover effect on Austria as $\frac{\widehat{\gamma}_t+\hat{l}_{WG}\widehat{\theta}_t}{1-\hat{w}_A\hat{l}_{WG}}$.

After steps 1 and 2 are implemented, we can check whether Assumption 3, i.e., the non-singularity of the matrix $\widehat{\Omega}$, holds. $\widehat{\Omega}$ in this example is given by

$$\widehat{\Omega} = \begin{pmatrix} 1 & -0.42 \\ -0.33 & 1 \end{pmatrix}$$

As $det(\widehat{\Omega}) = 0.86$, Assumption 3 holds in this application and we can now proceed to steps 3 and 4. Specifically, we need to find $det(\widehat{\Omega}_{WG,t})$ and $det(\widehat{\Omega}_{A,t})$ for each period, where $\widehat{\Omega}_{WG,t}$ and $\widehat{\Omega}_{A,t}$ are matrices obtained by replacing in $\widehat{\Omega}$ the vector of estimated effects $\widehat{\beta}_t$ in the first column for West Germany and in the second column for Austria, namely:

$$\widehat{\Omega}_{WG,t} = \begin{pmatrix} \widehat{\theta}_t & -0.42 \\ \widehat{\gamma}_t & 1 \end{pmatrix} \text{ and } \widehat{\Omega}_{A,t} = \begin{pmatrix} 1 & \widehat{\theta}_t \\ -0.33 & \widehat{\gamma}_t \end{pmatrix}.$$

The treatment and spillover effects for each period are given by $\frac{det(\widehat{\Omega}_{WG,t})}{det(\widehat{\Omega})}$ and $\frac{det(\widehat{\Omega}_{A,t})}{det(\widehat{\Omega})}$, respectively.

We conduce all the estimations using the package 'Synth' (Abadie et al. 2011) on the software R.

2.4 Results

This section describes the results both for West Germany and Austria, and conduces in-space placebo tests and robustness checks.

2.4.1 The treatment effect on West Germany

Abadie et al., 2015 find a negative effect of the reunification on West Germany per capita GDP that was reduced by approximately 7.67% per year on average with respect to the 1990 baseline level. Our iSCM results are not very different from the one of Abadie et al., 2015 and confirm their expectation about the potential direction of the bias, which implies an even more negative effect of reunification. Table 2.4 shows, for each post-reunification year, the effect in terms of per capita GDP for standard SCM, i.e., without having subtracted the bias due to spillover effects on Austria (first column), iSCM (second column), 'restricted' SCM, i.e., the version that excludes Austria from the donor pool (fourth column). The third column represents the bias between the iSCM and SCM, i.e., the share of spillover effect for Austria included in the standard version of SCM.
Our iSCM estimate implies a negative effect that is up to 1.50% larger than the one estimated with a standard SCM.
Figure 2.1 shows the difference between the trends in per capita GDP for iSCM (dark line), SCM (red line), and 'restricted' SCM (purple line). Even if the gap between the observed values and the 'restricted' SCM shows a even more negative effect, we can observe that the pre-treatment gap is farther from zero than those for the standard and inclusive SCM[2]. Figure 2.2 shows the per capita GDP trajectory of West Germany (dark line), the synthetic counterpart in the standard synthetic control version, i.e., including spillover effect (red dashed line), the 'restricted' synthetic control version, i.e., excluding Austria from the donor pool (purple dashed line), and the inclusive synthetic control version, i.e., not including the spillover effect (dark dashed line) on Austria.

[2]We remember that standard SCM and iSCM are identical in pre-treatment period because spillover effects due to German Reunification happen after the event.

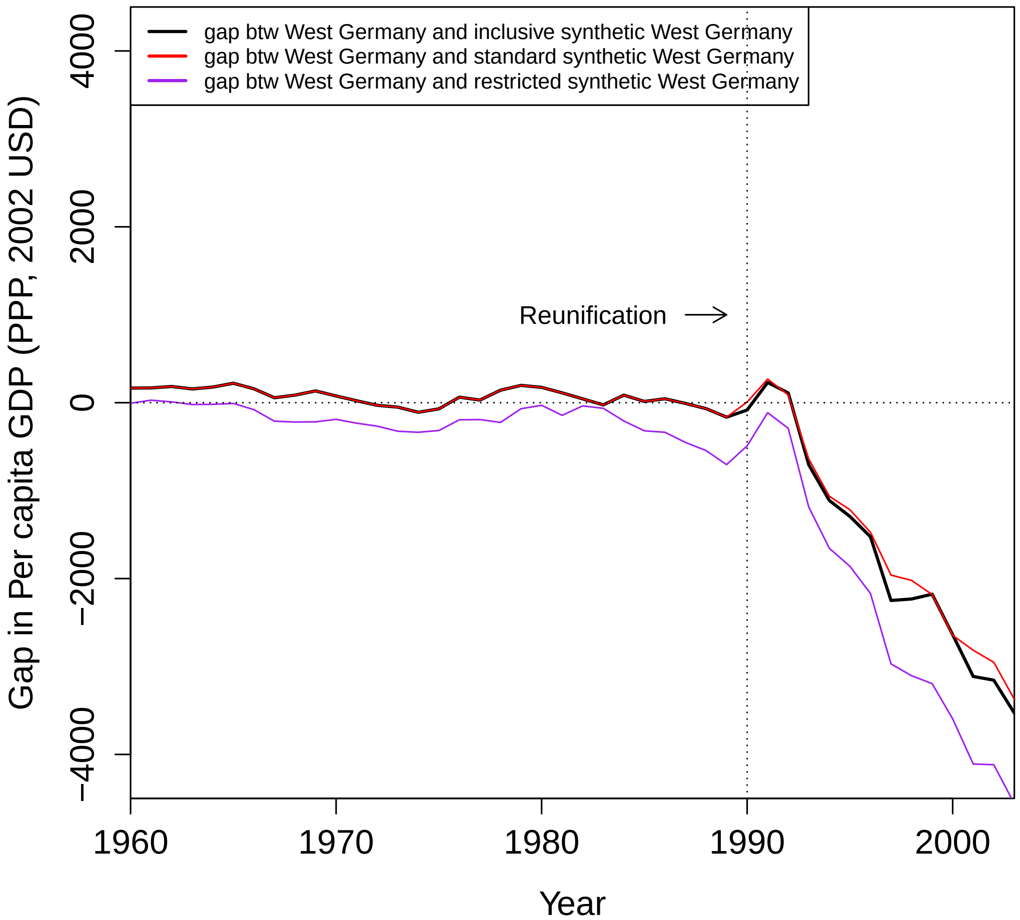


FIGURE 2.1: Estimated effects on West Germany

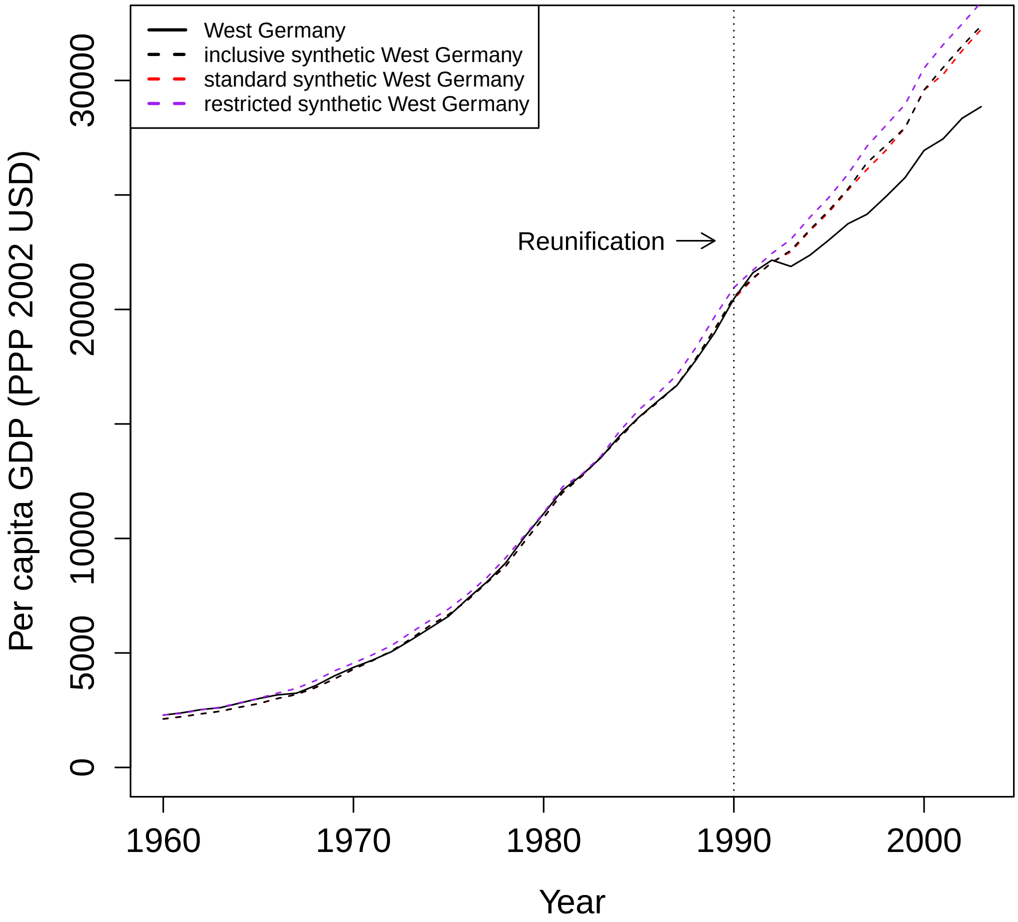


FIGURE 2.2: Trends in per capita GDP: West Germany, synthetic West Germany, inclusive synthetic West Germany, and 'restricted' synthetic West Germany

TABLE 2.4: Treatment Effects on West Germany

	$\widehat{\theta}_t^{SCM}$	$\widehat{\theta}_t^{iSCM}$	$\widehat{\theta}_t^{iSCM} - \widehat{\theta}_t^{SCM}$	$\widehat{\theta}_t^{resSCM}$
1990	7.58	-83.21	-90.79	-490.71
1991	268.31	229.89	-38.42	-113.50
1992	87.90	111.03	23.13	-291.56
1993	-642.23	-707.14	-64.91	-1187.41
1994	-1064.13	-1112.46	-48.33	-1656.09
1995	-1216.99	-1293.31	-76.32	-1860.16
1996	-1473.30	-1524.64	-51.34	-2169.88
1997	-1960.38	-2249.24	-288.86	-2970.69
1998	-2020.74	-2232.20	-211.47	-3104.82
1999	-2181.48	-2177.89	3.59	-3194.84
2000	-2645.30	-2638.79	6.51	-3595.01
2001	-2815.12	-3113.22	-298.10	-4109.12
2002	-2951.69	-3155.55	-203.86	-4116.73
2003	-3372.36	-3529.42	-157.06	-4559.62

2.4.2 The spillover effect on Austria

Table 2.5 shows the spillover effect on Austria, estimated with the iSCM approach, i.e., including West Germany in the donor pool and then eliminating the post-intervention effect. We observe a negative spillover on Austria's per capita GDP, confirming the previous conclusion on West Germany. Especially in 1997-1998 and 2001, the spillover is about 700 USD per year less than it would have been in the absence of reunification. Figure 2.3 shows graphically the gap between Austria and inclusive synthetic Austria (dark line). In Figure, we also show the gap between Austria and the standard synthetic control version that includes West Germany (red line), i.e., the treatment effect on West Germany, and the gap between Austria and the 're-stricted' synthetic control version, i.e., excluding the West Germany from the donor pool (purple line). Including West Germany in Austria's donor pool induces a bias, assuming that there is an effect on West Germany, see section (see 1.3.1). When we exclude West Germany from Austria's donor pool, the spillover effect is positive and similar in magnitude to the biased effect obtained by including West Germany. Moreover, a positive spillover effect it is not very likely (seeAbadie, 2021), thus, arguably, it is preferable to include West Germany and then eliminating the post-intervention effect by applying our iSCM.

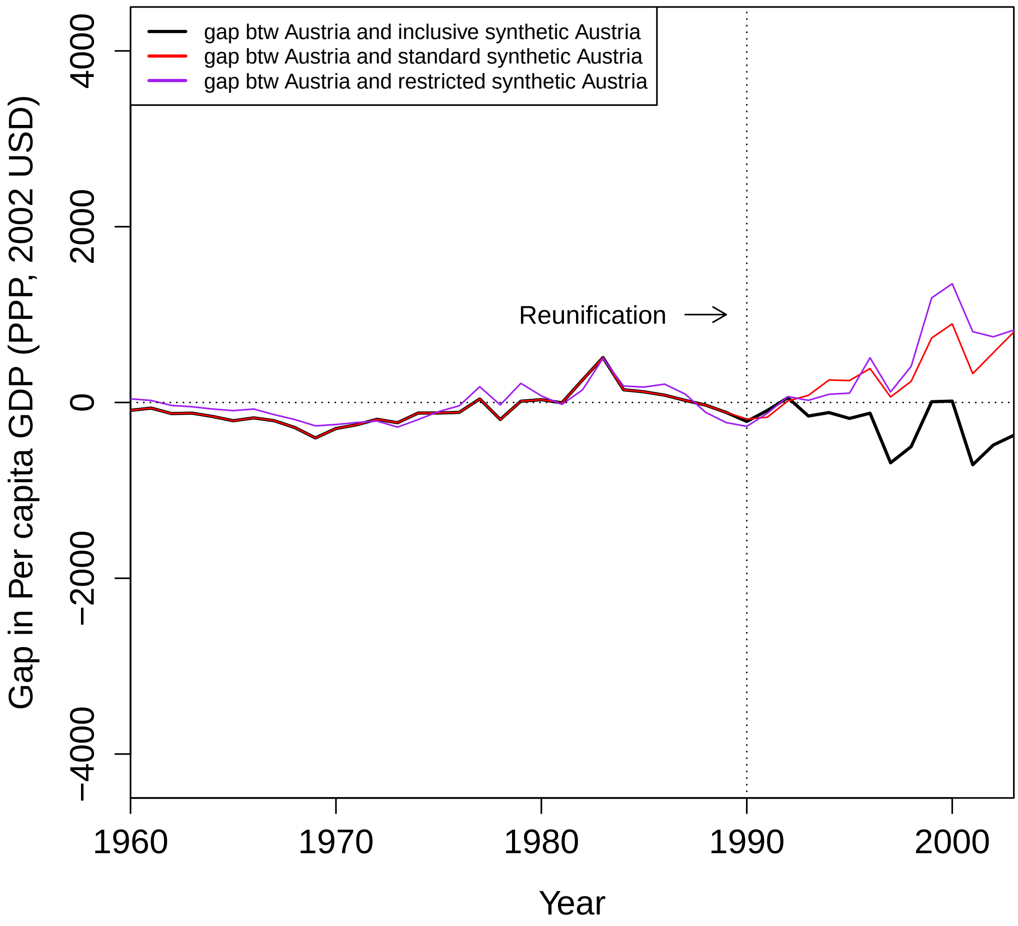


FIGURE 2.3: Estimated effects on Austria

TABLE 2.5: Treatment Effects on Austria

	$\widehat{\gamma}_t^{iSCM}$
1990	-215.83
1991	-91.33
1992	54.98
1993	-154.29
1994	-114.88
1995	-181.43
1996	-122.04
1997	-686.65
1998	-502.68
1999	8.52
2000	15.48
2001	-708.61
2002	-484.60
2003	-373.36

2.4.3 Inference and Robustness checks

Inference: in-space placebo

To measure our results' statistical significance, we propose in-space placebo tests, as shown in Abadie et al., 2015. i.e., we reassign the intervention artificially to each country in the donor pool. This allows us to compare the estimated effect on West Germany to the distribution of placebo effects obtained for OECD countries. If the estimated effect on West Germany is unusually large concerning placebos distribution, it is statistically significant.

Before running the placebo tests, we have to consider that the observed Austria's per capita GDP includes the spillover effect. So, we subtract from the Austria outcomes the spillover effect estimated with iSCM. Then, we can easily compute the ratio between RMSPEs in post and pre-reunification for each country, as described in the previous chapter. They measure the lack of fit between the observed outcomes for each placebo country and their synthetic controls.

Figure 2.4 shows the ratios between the RMSPEs in the post- and pre-reunification of West Germany and the donor pool. We can observe that West Germany's value is very high and the largest compared to the other countries in the donor pool. Table 2.6 shows the associated p-values, confirming a significant effect on West Germany. P-values give us information about the magnitude between the estimated effects and the placebo gaps in the donor pool. However, this procedure and associated p-values tell us only whether or not the estimated treatment effect is large relative to the distribution of placebo effects.

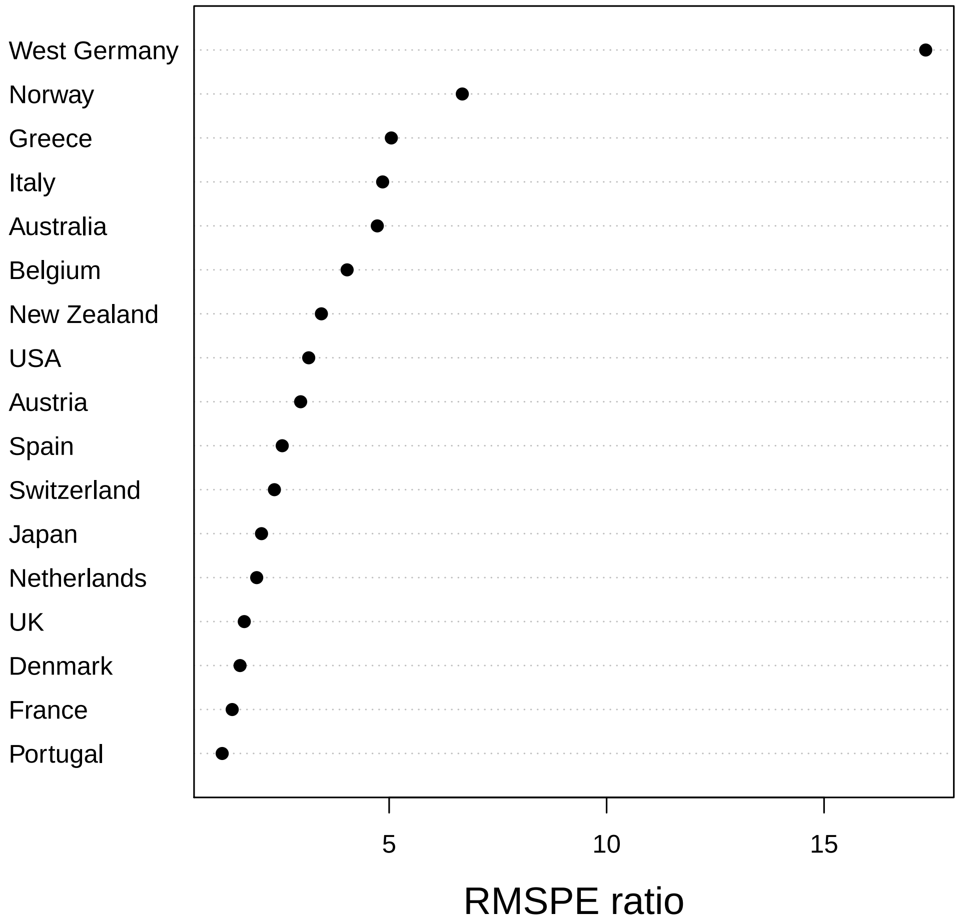


FIGURE 2.4: Ratio of post- and pre-reunification RMSPEs: West Germany and control countries

TABLE 2.6: P-values

	p-value
West Germany	0.058
Austria	0.529
Australia	0.294
Belgium	0.353
Denmark	0.882
France	0.941
Greece	0.176
Italy	0.235
Japan	0.706
Netherlands	0.765
New Zealand	0.412
Norway	0.118
Portugal	1
Spain	0.529
Switzerland	0.647
UK	0.824
USA	0.471

Robustness checks: three spillover units

The German reunification could have effects on other European countries. Albeit we cannot justify this affirmation, we propose a robustness test that considers other European countries with positive weight in the synthetic West Germany construction as possible affected countries. We consider only countries with positive weights because they are the only that could include a bias[3]. This would allows us to confirm that the effect on West Germany is an upper bound of the true effect.

So, we consider Switzerland and the Netherlands as well as Austria as potentially affected countries and implement the iSCM procedure, as described in the previous chapter.

Figures 2.5 and 2.6 show the trajectories and the effects on West Germany, respectively. As previously described, the red line represents the standard SCM, the purple one represents the 'restricted' SCM, i.e., excluding these three countries from the donor pool, and the dark one represents the iSCM.

[3]Excluding three countries from a donor pool of 16 countries, especially excluding the most similar, could not be advisable. Nevertheless, in Appendix B.2 we show points a and b of step 2 of the procedure 1.3.3 to verify the convenience in the use of iSCM.

The results, also shown in Table 2.7, confirm the negative nature of the spillover effects. The German reunification effect on West Germany when considering spillover effects on the three neighboring European countries is even larger than considering only the spillover on Austria.

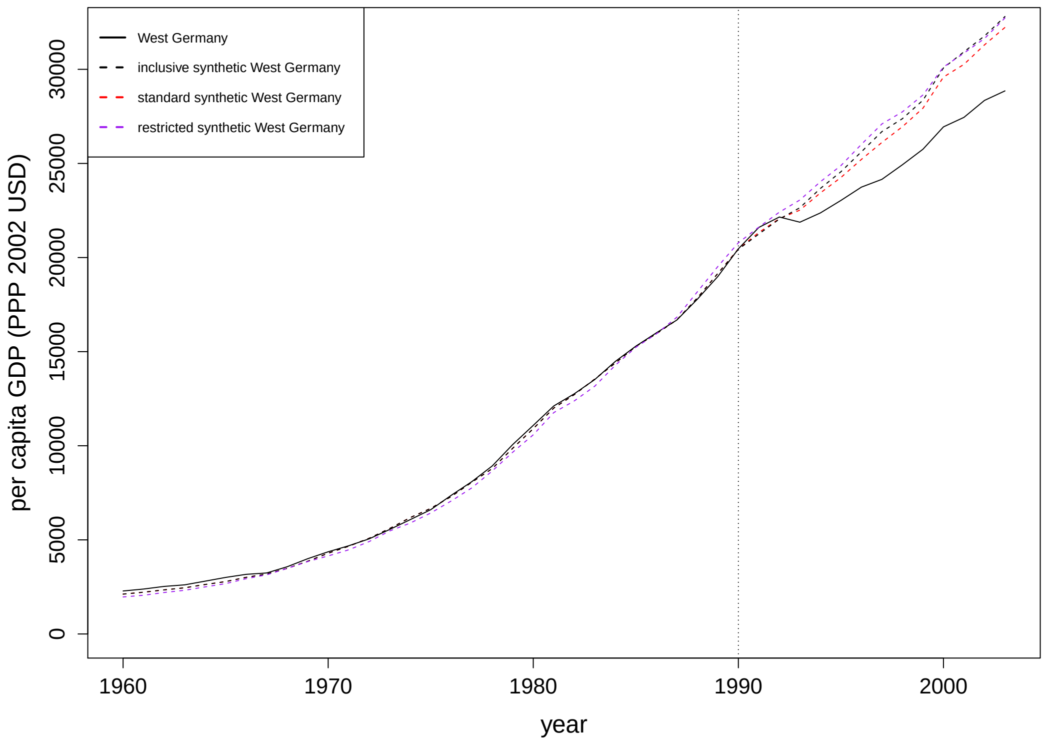


FIGURE 2.5: Trends in per capita GDP in the presence of three spillover units

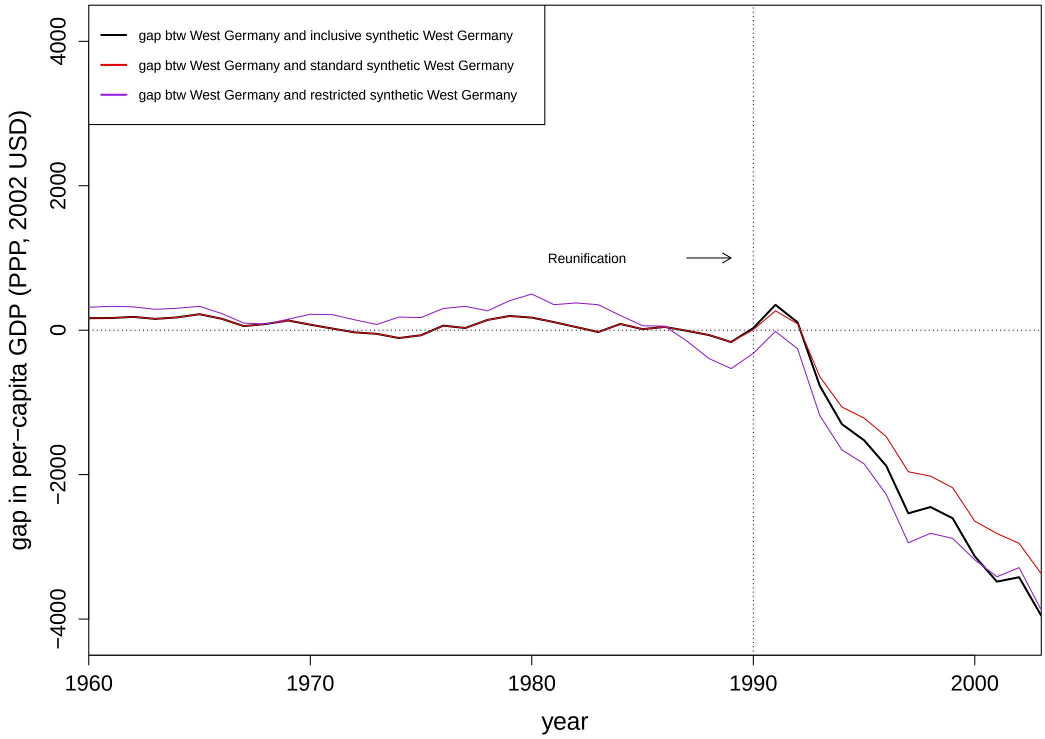


FIGURE 2.6: Estimated effects on West Germany in the presence of three spillover units

TABLE 2.7: Treatment Effects on West Germany eliminating spillover effects on Austria, Netherlands and Switzerland

	$\widehat{\theta}_t^{3spill}$
1990	28.92
1991	351.69
1992	108.86
1993	-768.84
1994	-1301.15
1995	-1523.84
1996	-1877.37
1997	-2536.62
1998	-2449.63
1999	-2605.05
2000	-3132.40
2001	-3483.03
2002	-3421.77
2003	-3953.96

Robustness checks: a different algorithm

To confirm the results, we change the algorithm to assess synthetic weights. We use the kernel balancing approach (KB), developed by Hazlett and Xu, 2018. This approach reduce the discretion of users and also match in the high-order features (e.g. variance, volatility, curviness) of the trajectories, ensuring that the distributions of pre-treatment trajectory as well as covariates are similar between the treatment and the reweighed control groups. It is more selective in the choose of controls. To further details on KB procedure, see the section 3.6 of the following chapter.
We follow the procedure 1.3.3 to judge whether it is more convenient implement the iSCM. First of all, we have to check if West Germany gives enough weight to Austria to have a large bias in estimating the treatment effect. As shown in Table B.3 in Appendix, West Germany gives an high weight to Austria (79%), even larger than using SCM algorithm. Then, we proceed to step 2. Once implementing the 'restricted' version of West Germany, i.e., excluding Austria from the donor pool, we look at the predictors bias ($X_1 - X0W$) and RMSPE comparisons. Table B.4 in Appendix shows that the standard version leads to a less bias than the 'restricted' one. Moreover the RMSPE in pre-treatment period for the standard version (equal to 219.51) is less than RMSPE in pre-treatment period for the 'restricted' version (equal to 368.21). We can affirm that including Austria in West Germany's donor pool is convenient.
Now we repeat the same procedure for Austria. Also Austria gives enough weight to West Germany (25%) to have a large bias in estimating the spillover effect, as shown in Table B.3 in Appendix, even if smaller than using SCM algorithm. Proceeding to step 2, we check the predictors bias ($X_1 - X0W$). The version including West Germany has a less bias than the 'restricted' version for most predictors. Moreover, the RMSPE for the former is 176.93, much lower than the RMSPE for the 'restricted' version, that is equal to 341.26. We can affirm that including West Germany in Austria's donor pool is convenient. Now we can follow with the iSCM procedure, as described in the previous section.
In table 2.8 we show the treatment effect on West Germany, confirming the even more negative effect eliminating the bias coming from the spillover effect on Austria. The spillover effect on Austria is shown in the fourth column.

Results are also represented in Figures 2.7 and 2.8 for West Germany and in Figure 2.9, that shows the effect of German reunification on Austria.

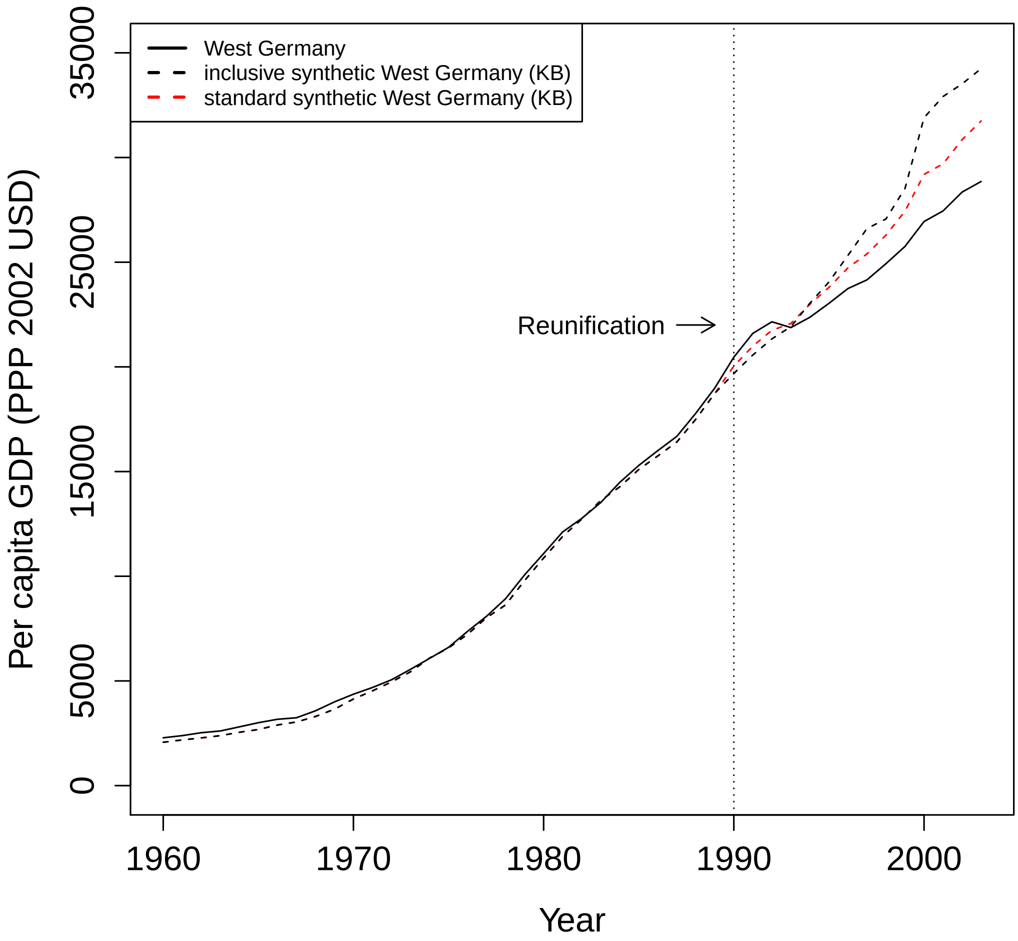


FIGURE 2.7: Trends in per capita GDP using Kernel balancing approach: West Germany, synthetic West Germany, inclusive synthetic West Germany

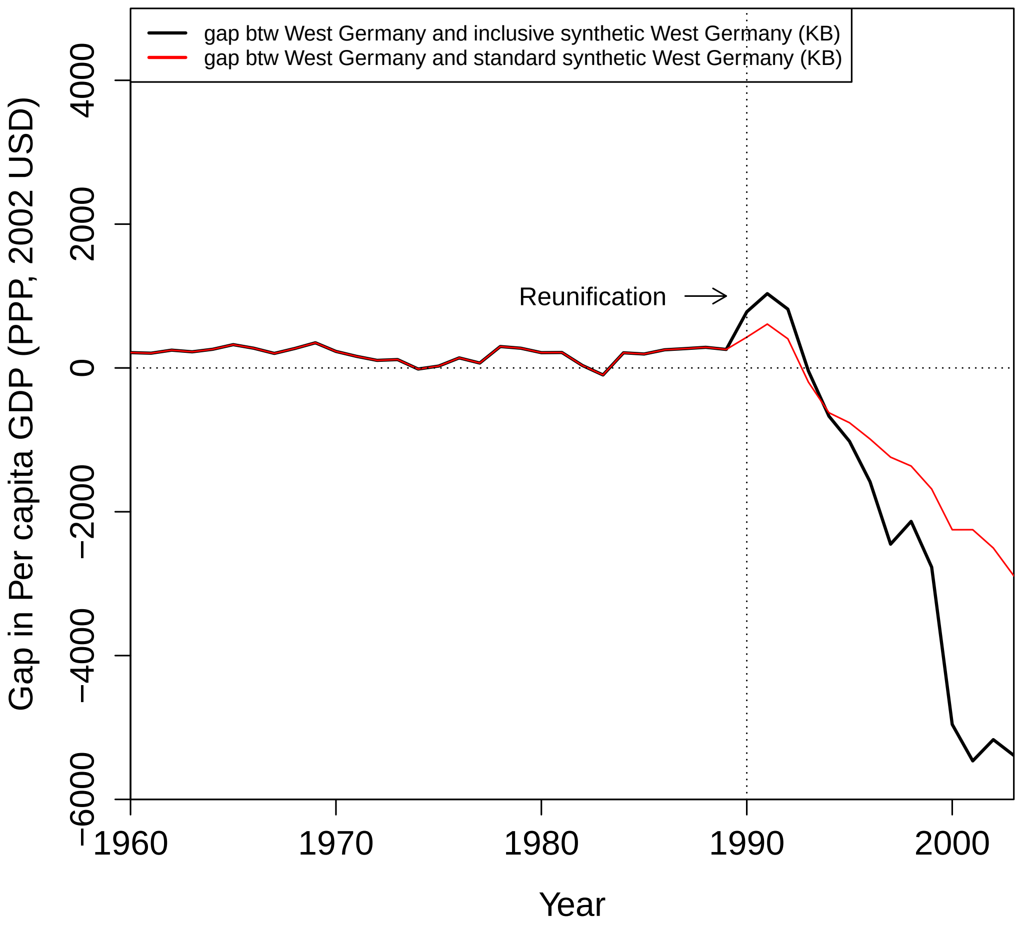


FIGURE 2.8: Estimated effects on West Germany using Kernel balancing approach

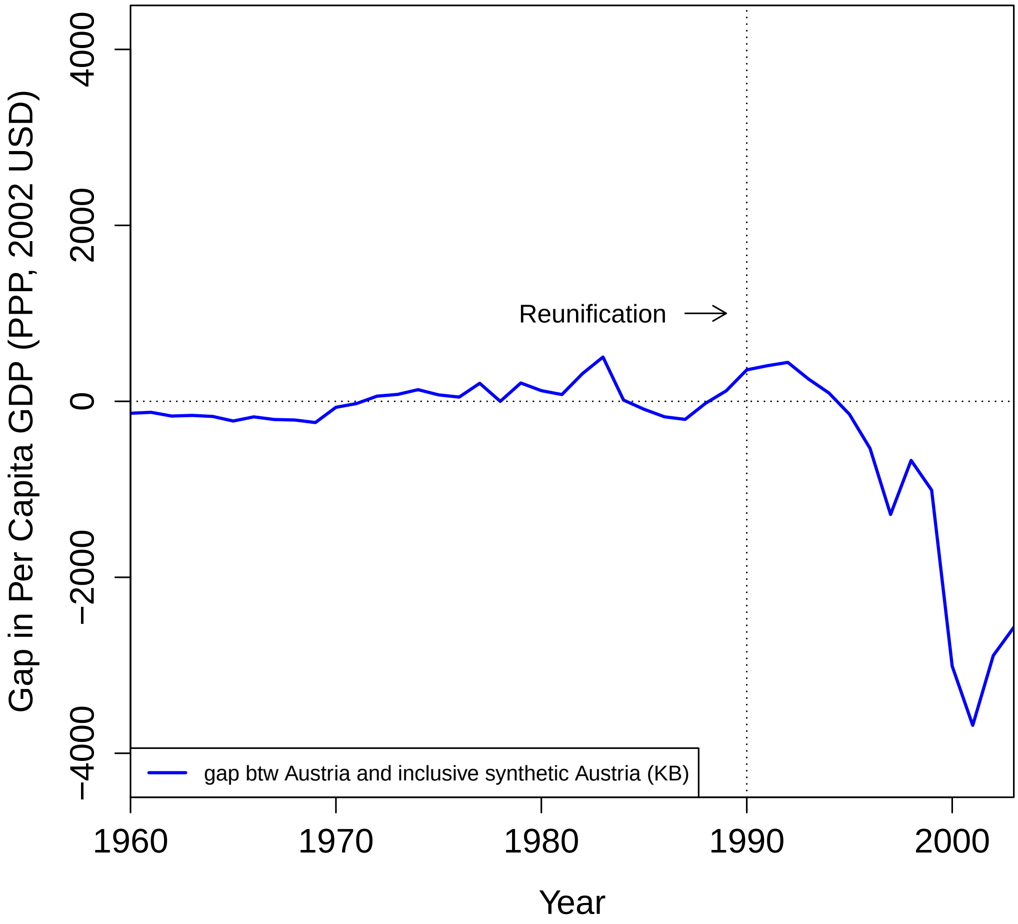


FIGURE 2.9: Estimated effects on Austria using Kernel balancing approach

TABLE 2.8: Treatment Effects on West Germany and spillover effect on Austria (KB algorithm)

	$\widehat{\theta}_t^{KB}$	$\widehat{\theta}_t^{iSCM(KB)}$	$\widehat{\theta}_t^{iSCM(KB)} - \widehat{\theta}_t^{SCM(KB)}$	$\widehat{\gamma}_t^{iSCM(KB)}$
1990	427.90	780.69	352.78	443.76
1991	610.21	1033.48	423.27	532.42
1992	404.99	817.53	412.54	518.92
1993	-196.73	-42.26	154.47	194.30
1994	-622.90	-671.02	-48.11	-60.52
1995	-762.15	-1020.33	-258.17	-324.75
1996	-988.59	-1583.11	-594.52	-747.83
1997	-1240.80	-2450.94	-1210.14	-1522.20
1998	-1363.93	-2133.77	-769.84	-968.35
1999	-1683.31	-2769.86	-1086.55	-1366.74
2000	-2250.12	-4957.30	-2707.17	-3405.27
2001	-2249.53	-5465.08	-3215.55	-4044.75
2002	-2503.84	-5168.99	-2665.15	-3352.41
2003	-2891.41	-5388.70	-2497.29	-3141.27

2.5 Conclusion

This chapter shows how iSCM works in empirical example. It confirms as this small modification of SCM is useful to refine the treatment effect and to estimate the spillover effect. It easily to implement, also using different algorithms and considering one or more possible affected units. Besides, we enrich the literature on the economic effect of German reunification, confirming expectations of Abadie et al., 2015 and Abadie, 2021 on the possibility to have negative spillover effects on Austria.

Chapter 3

What kind of region reaps the benefits of a currency union?

This chapter aims to estimate the regional economic impact of joining the euro area for the latecomers, i.e., the countries that adopted the euro after 2002. The use of regions as a unit of analysis and recent advancement in the SCM field allows us to tackle the literature on Optimal Currency Area (OCA), considering the core-periphery dynamics. We estimate the overall effect for the eastern European area as well as the disaggregated effect for every single region.

3.1 Introduction

The fall of the Berlin Wall not only gave rise to German reunification with effects on the Western economy but also marked the beginning of the fall of communism in central and eastern Europe.
In fact, in 1989, the Cold War between the capitalist Western Bloc and the communist Eastern Bloc was concluded, and the USSR's influence over communist Europe started to collapse. A new independence process began between 1990 and 1992 in a European integration perspective that saw a key step in 2004 with the EU enlargement to most eastern European countries. On 1 May 2004, Czech Republic, Estonia, Cyprus, Latvia, Lithuania, Hungary, Malta, Poland, Slovenia, and Slovakia joined the European Union (EU), while Romania and Bulgaria joined the EU three years later. Excluding Malta and Cyprus, all countries come from a historical path driven by the socialist

system.

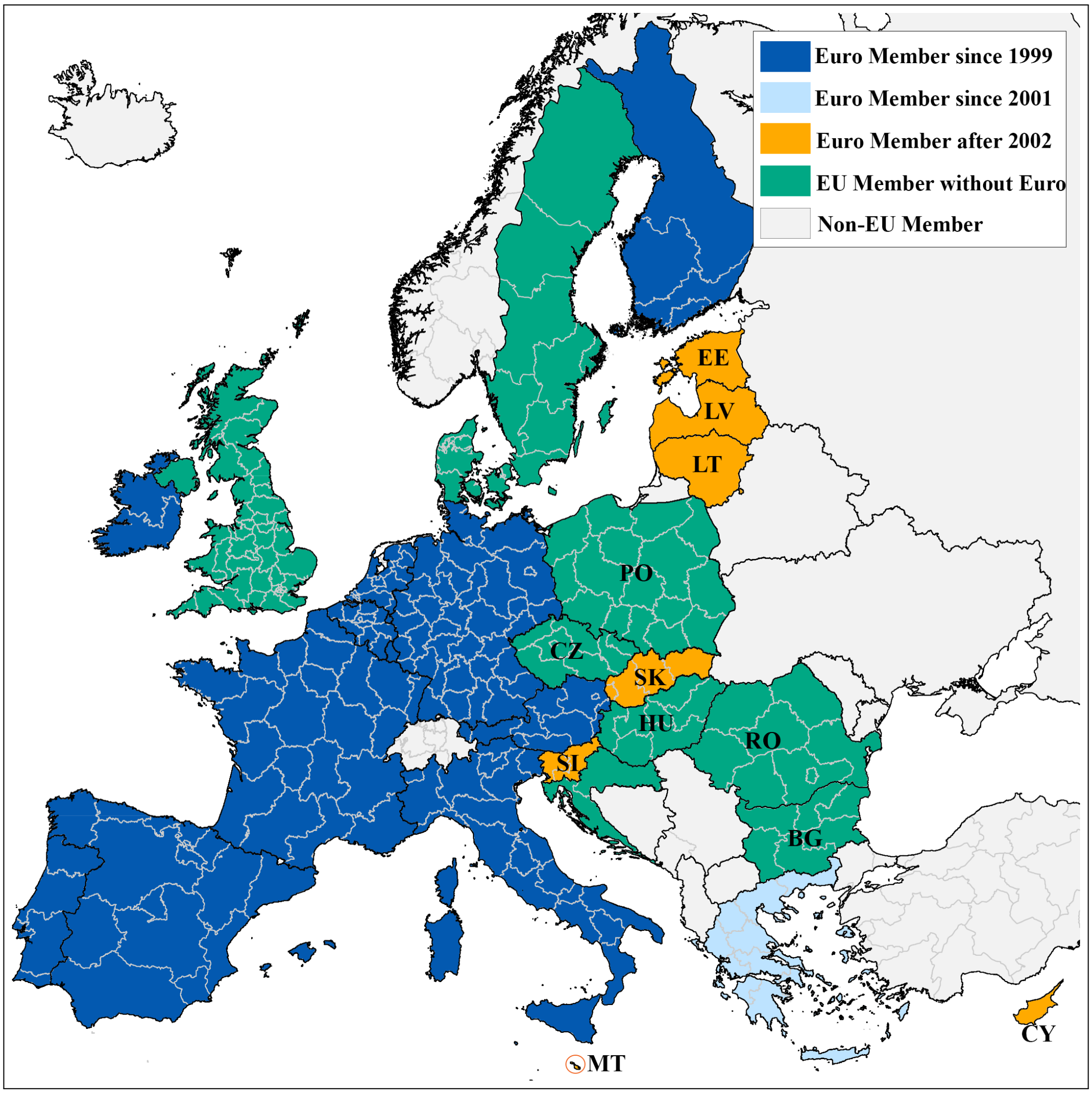


FIGURE 3.1: Political map of Europe showing the European countries that joined the euro (NUTS-2 level) by data of entry

Notes: The map shows the situation in 2015. At that time, the UK was still a member of the EU. Croatia joined the EU in 2013.

The EU integration process is strictly connected with euro adoption. The elimination of cross-border barriers to the free movement of goods, services, capital, and people cannot be complete when each member state has its own currency, some with floating exchange rates (see European Commission, 1990)[1].

[1]Dabrowski, 2019 remarks the marginal political influence over EU policy decisions of countries that decide to remain outside the European Monetary Union (EMU).

Nevertheless, for eastern European countries, the actual national sovereignty was a delicate issue after independence from the USSR. As highlighted by Ágh, 2017, the euro accession is viewed as a confirmation of their national sovereignty, which protects them against potential Russian aggression. On the other hand, eastern countries have only recently obtained national sovereignty and might be unwilling to give up monetary policy independence.
While joining the euro might represent an opportunity to close the large economic gap between the euro area countries and those in eastern Europe, it requires careful economic preparation. According to Artis et al., 2006, the euro area monetary policy would be ill-adapted to the needs of most eastern countries, with a counter-indication to EMU participation.
The monetary unification process seems to continue slowly towards the east of Europe. While Slovenia, Slovakia, and the Baltic countries joined the EMU and, as of December 2020, Bulgaria, Romania, and Croatia have expressed their willingness to join the euro area[2], other eastern countries have a purely pessimistic approach like the Czech Republic according to Rozmahel et al., 2013. Poland's statements regarding the euro might be considered careful regarding the current state of Maastricht criteria' fulfillment. These criteria involve: a high degree of price stability (average inflation over one year before the examination not more than 1.5 percentage points above the rate of the three best-performing EU countries), a sound fiscal situation (public deficit below 3 percent of GDP), converged long-term interest rates (long-term interest rate not more than 2 percentage points above the rate of the three best-performing EU countries in terms of price stability), and exchange rate stability (participation in the Exchange Rate Mechanism (ERM II) for two years without severe tensions). ERM II mimics the euro area conditions, thereby helping non-euro area Member States prepare for satisfying such criteria. By following ERM II, countries accept to limit their monetary policy; in fact, they cannot move the exchange rate.
Estonia, Latvia, Lithuania, Slovenia, and Slovakia started participating in ERM II between 2004 and 2005, even if joined the euro in different times, between 2007 and 2015.

[2]Bulgaria and Croatia sent a letter of intention respectively in July 2018 and in July 2019 regarding ERM II participation, and in July 2020 the ERM II parties agreed to include Bulgaria lev and the Croatian kuna in the ERM II mechanism. According to the National Plan to Changeover to the Euro, Romania has scheduled 2024 as the date for euro adoption. As of December 2020, Romanian is not part of ERM II.

In our analysis, we try to answer questions like: which regions gained from joining the euro area? Do economic crises make these gains vanish?
Two are the important novelties in this study:

1. We are the first, to our knowledge, to use a counterfactual approach to investigate the regional impact of joining the euro area by using NUTS-2 regions as the unit of analysis[3]. All previous studies have used country-level data (see, among others Fernández and Garcia-Perea 2015; Puzzello and Gomis-Porqueras 2018; Gabriel and Pessoa 2020). This is a crucial step forward as it allows us to evaluate the spatial heterogeneity of the impact, improving the estimate accuracy, and better investigate the theoretical predictions related to the currency union impact on local economies.

2. The use of the kernel balancing (KB) approach introduced by Hazlett and Xu, 2018. This is a counterfactual method that improves on the Synthetic Control Method (SCM) (Abadie and Gardeazabal 2003, Abadie et al. 2010) by adopting a more sophisticated reweighing algorithm and explicitly allowing the analysis of multiple treated units. KB estimates the counterfactual scenario, i.e., what would have happened to the latecomer central and eastern European countries – Estonia (1 region), Latvia (1 region), Lithuania (1 region), Slovenia (2 regions), and Slovakia (4 regions) - if they had not joined the euro area. Then it measures the effect as the difference between the factual and counterfactual situation. Our panel dataset covers all NUTS-2 regions belonging to central and eastern European countries in all years from 1993 (two years after eastern European countries became independent from the Communist Bloc) to 2015.

We find that the adoption of the euro brought about a positive effect, which was, however, dampened by the Great Recession. The individual regional estimates show heterogeneous returns from joining the currency union, also within a single country. The real 'winner' is the Bratislava region in Slovakia, which garnered a great advantage from joining the euro area, also during the

[3] We consider regions at NUTS-2 level and adopt the NUTS 2013 regional classification. The NUTS classification (Nomenclature of Territorial Units for Statistics) is a system for classifying the economic territory of the EU.

economic crisis. This finding is in line with New Economic Geography (NEG) predictions, as the Bratislava region is the only 'core' area: among the treated units, it is the only urban region bordering on EU-15[4], and it is the wealthiest region. On the contrary, Eastern Slovakia registered a slight loss, while the other two Slovak regions did not gain nor lose, being a 'periphery' not only in Europe but also inside their country. Slovenian regions had not gained from the euro before the crisis and registered consistent losses afterward. Baltic countries recovered losses experienced during the Great Recession, but only Lithuania obtained a gain.

The chapter is organized as follows. Section 3.2 presents an overview of central and eastern European countries, highlighting their common history and differences among and within countries. Section 3.3 describes the pros and cons of joining a currency union, presenting the OCA and the NEG theories; while Section 3.4 reports the most important studies that estimate the effect of euro adoption on economic growth. Sections 3.5 and 3.6 define data and methodology, respectively. Section 3.7 presents results both for the overall and the disaggregated effects. Sections 3.8 and 3.9 implement in-space placebo tests and different robustness checks, respectively. Lastly, Section 3.10 concludes.

3.2 Central and eastern Europe: an overview

The central and eastern European countries followed a development model aimed at integration since the collapse of the communist regime. Even with differences, they shared common history and characteristics.

The state of *Slovenia* was created in 1991. From 1945 was part of the Socialist Federal Republic of Yugoslavia, a federation driven by Josip Tito. It was sided with the Eastern Bloc until the Tito–Stalin split of 1948. Then, it pursued a policy of neutrality with a market-based socialist economy. In 1980, with the death of Tito, its economy started to collapse. Slovenia, the wealthiest state, together with Croatia, started to pursue the independence idea. In

[4] 15 was the number of Member States in EU before the accession of ten candidate countries on 1 May 2004. The EU15 comprised the following 15 countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden, and the United Kingdom.

1990, there were the first free multiparty elections for Slovenia, which followed a liberal democratic political system and a market economy. After the referendum for independence was held in 1990. It was declared independent on 25 June 1991.

The *Slovakia* and the *Czech Republic* were part of Czechoslovakia until 1992. Czechoslovakia was created in 1918, but between 1939 and 1945 ceased to exist. In 1945 it was reestablished and became part of Eastern Bloc with a planned economy. In 1989, with the Velvet Revolution, the socialist system fell, and in 1992 it was dissolved by mutual consent of Parliament. On 1 January 1993, it was split into two independent states: the Czech Republic and the Slovak Republic.

The Baltic state's history followed a similar path. Before 1918 *Estonia*, *Latvia* and a part of *Lithuania* belonged to the Russian empire. While the rest of Lithuania belonged to the Prussian empire. In 1918, they became independent states and remained so until the beginning of the World War II when they were invaded and annexed to the Soviet Union. After a brief occupation by Nazi Germany, Baltic countries were reoccupied by the Soviet Union, becoming officially part of the USSR. Gradually started, the independence process was concluded between August and September 1991 for all three states.

Poland re-emerged in 1918 after more than a century of partitions among Austria-Hungary, the German, and the Russian Empires. In 1939, was invaded by Nazi Germany and the Soviet Union. After the end of the II World War, it became a communist satellite state of the Soviet block. During the 1980s, it started a transition process from a communist planned economy to a democratic capitalist economic system that was concluded in 1989 with the creation of the modern Polish state.

In 1945, also *Bulgaria* became communist satellite state until 1990 when there were the first free elections.

Hungary was created in 1918. Invaded by the Soviet Union, in 1945 it established a communist government until 1989 when the Parliament revised the constitution and reformed its economy.

The current-day borders of *Romania* date back to 1918. In 1945 it was established a communist system that fell in 1989 after the Romanian revolution when democratic and free-market measures were introduced. Romania was the only state where the transition from communist was violent, with a revolution and the killing of the leader Ceauşescu in 1989.

All these states are really similar to each other (Artis et al. 2006), poorer than EU-15, rural, small in size – except for Poland – relative to EU-15, with a lesser efficient national and regional innovation systems (Kravtsova and Radosevic 2012). Despite similarities, they all experienced a more or less deep recession during the transition from the preceding centrally planned regime, then followed by an expansionary path. Different transition levels concern economic development, institutions, the stability of democracy, and civil society development. For example, Artis et al., 2006 observe that Slovakia was the most progressive country in central Europe at the beginning of the 2000s, while Slovenia did not perform well in economic terms.
However, the economic differences within central and eastern countries were even more remarkable than those across countries. For example, in Figure 3.2, the focus is on 2003[5] per capita GDP at the NUTS-2 level where there are clear differences within countries. Besides, although eastern countries are generally considered peripheral, the use of the regional level allows splitting these areas into core and peripheral regions. Figure 3.3 maps core and peripheral eastern areas, where core regions are those with a high level of urbanization[6].

After the transition period, all these states joined the EU in 2004, except Romania and Bulgaria that joined in 2007.
As can be observed from Table 3.1, Estonia, Latvia, Lithuania, Slovenia, and Slovakia started participating in ERM II between 2004 and 2005, while they joined the euro between 2007 and 2015. Indeed, the Baltic countries adopted the euro after a long period from the entrance in ERM II. Nevertheless, the exchange rate of their currencies with respect to the euro remained unvaried, also during the Great Recession.

[5] We choose 2003 as it is the year before the EU entrance for most states.

[6] Data on urbanization are taken from Jonard et al., 2009. The regions are classified in 3 classes (rural, intermediate, and urban) on the basis of the share of population living in rural municipalities or located in urban centers as developed in the OECD methodology.

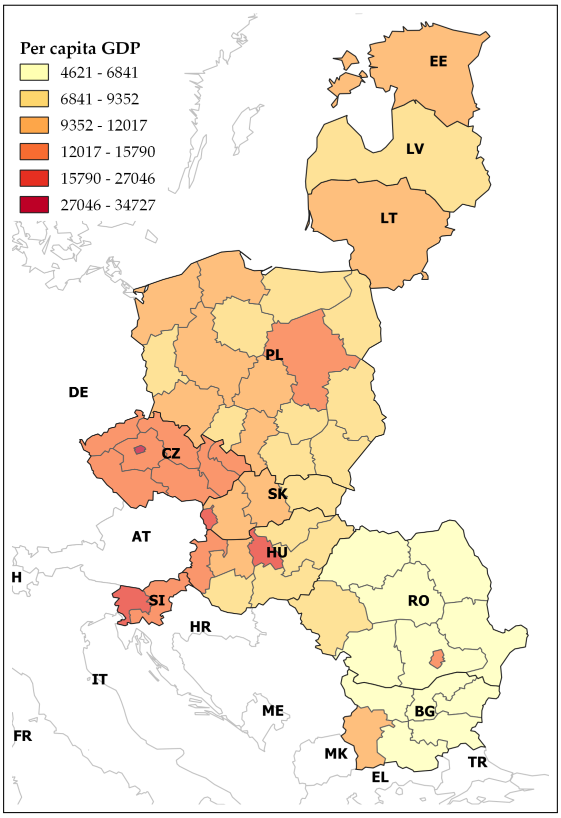


FIGURE 3.2: Level of 2003 per capita GDP in the eastern euro area by NUTS-2 level.

TABLE 3.1: Eastern European countries

Country	UE	ERM II	EMU	NUMBER OF NUTS-2
TREATED				
Slovakia	2004	2005	2009	4
Slovenia	2004	2004	2007	2
Estonia	2004	2004	2011	1
Lithuania	2004	2004	2015	1
Latvia	2004	2005	2014	1
Total				9
CONTROLS				
Bulgaria	2004	-	-	6
Poland	2004	-	-	16
Czeck Republic	2004	-	-	8
Romania	2004	-	-	8
Hungaria	2004	-	-	7
Total				45

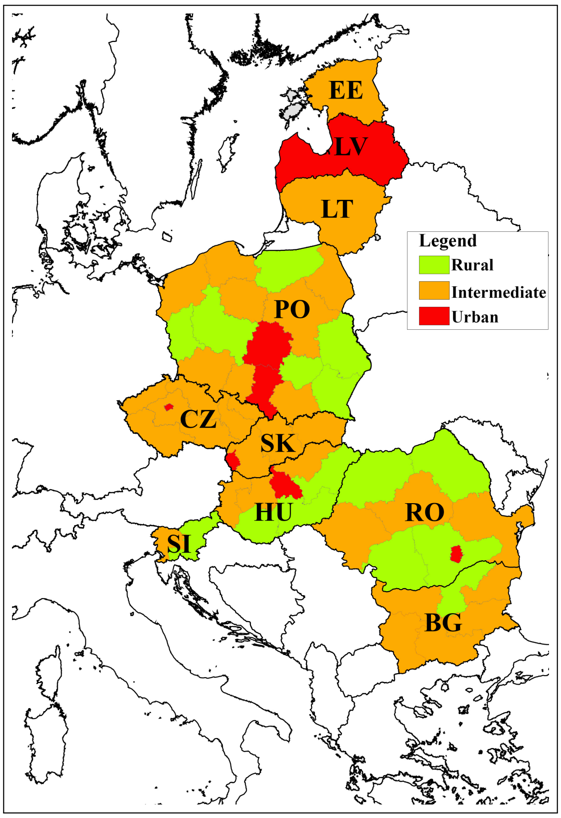


FIGURE 3.3: Level of urbanization in the central and eastern European area by NUTS-2 level. Source: Elaboration of data by Jonard et al., 2009

3.3 What are the pros and cons of joining a currency union?

Before analyzing if the euro adoption has brought benefits to the eastern European regions, let us understand what joining a monetary union entails.
At a time of sizable adverse shocks affecting the global economy, such as the Covid-19 pandemic or the Great Recession, monetary policy gains popularity rekindling the unending debate on the pros and cons of being part of a currency union. In general, the benefits of joining a currency union concern enhanced cost-effectiveness and reduced risk of doing business. Furthermore, strengthening the Member States' competitiveness on a global scale eliminates exchange rate risk and reduces the weight of interests for countries with a large public debt. On the other hand, the most considerable price to pay is the loss of complete sovereignty in monetary policy decisions. Thus, Member States can no longer resort to currency appreciation or depreciation to handle asymmetric external shocks, for example, by devaluing their currencies to slow imports and encourage exports. This negative effect is reinforced by the presence of wage rigidity and weak labor mobility, which are generally features of euro area countries. What is more, in the case of limited economic integration, monetary policies within a currency area will be ineffective and unsuitable for dealing with the countries' heterogeneity. According to the OCA theory, first developed by Mundell, 1961, asymmetric negative shocks stress this issue. For instance, the European sovereign debt crisis produced winners and losers at the country level and even more at the regional level due to the lack of similarity of economic structure and synchronization of the economic cycles that make centralized monetary policy decisions unsuitable for everyone. Although countries joining the euro might presume to reach symmetry of business cycles with monetary integration,[7] this process could result in either tighter or looser correlations of national and regional business cycles. Albeit regions are not directly affected by monetary policy decisions, participation in the euro area indirectly impacts regions' competitiveness. According to Hallet, 2004, the initial static integration effects of the euro, as the reduction of trade costs, may differ across regions and lead to dynamic integration effects on growth, employment, welfare, and thus

[7] For example, according to the 'Lucas critique', joining a currency union can be seen as a policy shock that changes the agents' economic expectations.

changing the spatial structure of production.

The neo-classical theory highlights the advantages of a currency union for peripheral regions, as it enhances the convergence process by attracting more investments (Barro and Sala-i-Martin 1992)[8]. This is to be achieved via the compensation of the localization disincentive with wage differentials. Frankel and Rose, 1998 refine the neo-classical framework and propose the endogeneity of the OCA criteria, affirming that a country can satisfy such criteria ex-post rather than ex-ante. In fact, they suggest that joining a currency area leads to more trade, increasing the degree of business cycle synchronicity and boosting net welfare (Rose and Van Wincoop 2001).

On the contrary, according to the NEG theory, economic integration favors the concentration of activities in core areas and, therefore, does not lead to synchronized business cycles. When firms produce more efficiently, and workers enjoy higher welfare by being close to large markets, which are those where more firms and workers locate: this engenders a cumulative causation process which increases regional differences (Puga 2002). Therefore, in compliance with the NEG theory, regions more open to trade and with better access to new markets, such as port cities and border regions, should experience more significant gains from adopting a single currency[9].

In Europe, the economic integration process started with the Single Market, and the euro adoption can be considered an accelerator for this process. Thus, if an increase or a decrease was observed in regional disparities after the set-up of the Single Market, we expect that the currency union accelerates this dynamic[10]. As reported by Capello et al., 2018, many studies demonstrate that the eastern enlargement of the EU increased intra-national disparities in favor of metropolitan and core areas. Therefore, we expect that the Eastern enlargement of the euro area will reinforce such a trend.

[8] Solow, 1956 and Swan, 1956show that under a certain assumption, income differentials across countries disappear in the long run. However, Barro and Sala-i-Martin, 1995 demonstrate that regions do not necessarily converge on the same equilibrium in the case of heterogeneous structural characteristics.

[9] McKinnon, 1963 was the first to put forward the importance of the high degree of openness to reap the advantages of an OCA. Moreover, Forlati, 2015 highlights potential improvements for a group of small open economies of entrusting the monetary policy to one single authority.

[10] The expected advantages of central European regions to attract production factors from the periphery were discussed during the Maastricht Treaty negotiations. This led to introducing the European Structural and Cohesion Funds, which target the least developed European Union regions.

In line with NEG predictions, Bayoumi and Eichengreen, 1993 argue that the Economic and Monetary Union (EMU) would disadvantage the least developed regions, with the benefits accruing to the most developed core areas. Fingleton et al., 2015 highlight the importance of the regional aspect in the context of an OCA: national economies are considered merely as aggregates of their constituent regional and sub-regional components. So, while countries might meet the OCA conditions, their regions might not, and vice versa[11].

Given the importance of this topic, recent literature considers core-periphery patterns in evaluating the economic effect on a country of joining a currency union. Nevertheless, it surprisingly ignores the regional dimension of integration and convergence[12]. This chapter seeks to fill this gap in the literature. In light of the substantial heterogeneity across European regions, it is crucial to assess the detailed economic impact of joining a currency union and how it changes during a crisis period given the limitation on the use of the monetary policy. Our work aims at estimating the regional economic impact of joining the euro for latecomer eastern countries. Choosing these countries has many advantages for identifying an adequate control group in a counterfactual approach. In fact, this allows comparison with countries with a similar economic and cultural structure, all in transition from preceding centrally planned regime, which belong to the European Single Market and which all previously suffered the shock due to the creation of the euro area, even without belonging to it.

[11]Mundell, 1961 highlights that an OCA could be several states, regions of several states, or regions inside a single state.

[12]The regional dimension was also 'forgotten' by governments when deciding whether to join the euro area. Fingleton et al., 2015 affirm that there are three potential explanations for this: OCA theory was ignored, modified, or cast aside. In the first case, in favor of the political project; in the second case thinking of an 'endogeneity' version (Frankel and Rose 1998 states that potential member countries did not have to meet certain optimal conditions ex-ante but would instead form an OCA ex-post); in the last case because the 1990s theory focused on the neoclassical determinants rather than on the business cycle.

3.4 Literature review

Previous studies on the causal impact of joining the euro are carried out at the country level and mostly concern the early adopters. In this review, we first consider studies on the early-adopters and then articles on the late-adopter countries.

Puzzello and Gomis-Porqueras, 2018 use the SCM to provide estimates of the effect of the euro on the income per capita of six early adopters before the global financial and Eurozone crises took place. They find that Belgium, France, Germany, and Italy have lost from adopting the euro. In contrast, both the Netherlands and Ireland are better off after euro adoption. Moreover, they establish that trade is the main channel through which currency unions increase income growth. Gabriel and Pessoa, 2020 also consider trade one of the main channels even though they state that only Germany and Ireland obtain net trade benefits. Besides, they extend the Puzzello and Gomis-Porqueras, 2018 analysis to the twelve Member States which joined the euro before 2002, showing a substantial economic gain only for Ireland. Verstegen et al., 2017 used a similar approach to investigate the benefits of real GDP per capita from participation in the EMU. Their estimates suggest that, until the Great Recession, all countries, except for Italy, gained from being in the EMU, while, during the crisis, several Member States suffered losses from joining the euro. This impact is substantial and even statistically significant for Greece, Italy, and Spain. A similar evaluation strategy was used by Fernández and Garcia-Perea, 2015 who find that the euro area did not produce the expected permanent increase in GDP per capita. Their estimates suggest that peripheral countries (Spain, Greece, and Ireland) registered positive and significant gains up to the debt crisis, except Italy and Portugal. In contrast, central European countries (the Netherlands, Germany, and Austria) did not seem to obtain any gains or losses. A different approach is used by Drake and Mills, 2010 who decompose the euro area GDP into a trend and a cyclical component. They find that the adoption of the euro reduced the trend rate of growth of the Eurozone economies, both during the Maastricht nominal convergence phase and during the period from 2001 to 2005. Giannone et al., 2010 adopt a Bayesian Model Averaging approach to evaluate the EMU growth path, based on the past distribution and conditioning of external developments. Their results show that the euro area's average growth from 1999 to 2006 was slightly lower than what they would have expected. Country differences are small and come from different degrees of competitiveness, real interest rates, and other economic characteristics. Another significant contribution that underlines the heterogeneity of the impact is the study by Fingleton et al., 2015. They investigate the vulnerability and resilience of regions in the Eurozone to economic shocks, such as the Great Recession. Using predictions based on dynamic spatial panel models, they find a considerable difference between peripheral regions that suffered the most during the crisis period, and central regions, that are more resilient. Concerning late-adopters, in our knowledge, there are only two studies. Backé, Dvorsky, et al., 2018 adopt a qualitative approach to investigate the economic impact of the enlargement of the euro area to include Central, Eastern and South-Eastern Europe (CESEE) Member States. They suggest that joining the euro area has not had a dampening effect on Slovakia or the Baltic countries (Estonia, Latvia, and Lithuania). Slovenia went through a more extended boom-bust cycle, with a second recession in 2012-13, before pursuing a dynamic growth path. The results of Slovakia are also confirmed by Žúdel and Melioris, 2016, who, using the SCM, quantify a gain approximately equal to 10% in terms of GDP per capita from joining the euro.

3.5 Data and Sample

In this study, we consider as treated the regions belonging to latecomer countries that adopted the euro after 2002[13]. As shown in Figure 3.1, we consider only the eastern European countries, i.e., Estonia (1 region), Latvia (1 region), Lithuania (1 region), Slovenia (2 regions), and Slovakia (4 regions), for a total of 9 treated regions. Our initial donor pool - the set of potential comparison units - includes all regions belonging to the EU countries that have not adopted the euro. We then restrict the donor pool to only eastern EU countries that are not in the euro area, i.e., Bulgaria (6 regions), Czech Republic

[13]We do not consider Malta and Cyprus as they have specific features that are difficult to recreate using a counterfactual approach. They are islands in the Mediterranean Sea and have historical and economic features quite different from the eastern European countries, which make up the core of our analysis. However, in Appendix C.8, we report the analysis concerning Malta and Cyprus.

(8 regions), Hungary (7 regions), Poland (16 regions), and Romania (8 regions), for a total of 45 regions[14]. We exclude Croatia as it joined the EU only in 2013. All the countries considered, both treated and control, have experienced a similar historical path, as described in section 3.2. This allows us to build a counterfactual scenario that mimics what would have happened to the regions treated in the absence of treatment. As suggested by Abadie et al., 2015, because comparison units have to approximate the counterfactual situation, it is important to restrict the donor pool to units with outcomes that are thought to be driven by the same structural process as for the treated units and that were not subject to different structural shocks affecting the outcome variable during the sample period of the study.

In our empirical analysis, the Great Recession hit all eastern countries in the ex-post period; therefore, we assume that the recession represented a common negative shock that affected eastern EU Member States similarly[15].

The eastern EU countries joined ERM II – here considered as the actual treatment – between 2004 and 2005, allowing for a pre-treatment period which ranges from 11 to 12 years. In particular, Slovenia, Estonia, and Lithuania entered ERM II in 2004, and Latvia and Slovakia in 2005[16].

Our main data source is the Cambridge Econometrics' European Regional Database (ERD) from 1993 to 2015, which consists of a wide range of economic and demographic indicators for the EU countries at the NUTS-2 level. The analysis also relies on data from Eurostat, PBL Netherlands Environmental Assessment Agency[17] - a trade database (Thissen et al. 2013) that determines interregional trade among 256 NUTS-2 regions and 59 sector categories from 2000 to 2010 - and the European Quality of Government Index

[14]Baltic countries, i.e., Estonia, Latvia, and Lithuania, are classified by one NUTS-2 region. Nevertheless, even for them, the use of the level NUTS-2 as the unit of analysis is important because using regions in the donor pool instead of countries makes it possible to create a more credible counterfactual scenario.

[15]Alessi et al., 2019 show that heterogeneous resilience at the crisis across EU countries, even though, in the short-run, the economic impact was similar for the majority of eastern countries, except for Poland that bounced back promptly from the negative shock. Another potential difference across eastern regions is the per capita amount of funds received from the EU regional policy. However, EU regional policy financial support is inversely proportional to the level of wealth. Therefore, as we control for GDP per capita in our analysis, we are implicitly controlling for differences across regions due to the EU regional policy funds.

[16]We consider entrance in ERM II as the beginning of the 'euro treatment' because the monetary policy is de facto limited and also to take into account the anticipation effects.

[17]PBL Netherlands Environmental Assessment Agency is the national institute for strategic policy analysis in the fields of the environment, nature, and spatial planning.

(EQI) [18] - that concerns citizen-based perception and experience with respect to corruption, quality, and impartiality in terms of education, public health care, and law enforcement (Charron et al. 2014)[19].

To capture the economic impact, we use the GDP per capita adjusted at Purchasing Power Standard (PPS). To identify the exogenous predictors of the economy, we control for: population, total hours worked per employee, employment rate on active population, compensation of employees, labor productivity, the share of gross value added (GVA) on the primary sector, the share of GVA on the tertiary sector, the share of old (65+) population, the share of foreigners, trade openness, trade balance, and EQI[20]. Description related to data is in Table 3.2.

[18] We thank Andres Rodríguez-Pose for providing us with these data.

[19] Weak institutional capacity is perceived as the key inhibitor in many lagging regions, so the EQI is a direct determinant of economic growth (Rodrıguez-Pose and Garcilazo 2015).

[20] Concerning trade, there are no data at the NUTS-2 level for Bulgaria, Romania, or Slovenia. We impute the missing regional data by allocating the national trade figure on the basis of the GVA in manufacturing. Concerning EQI, as data at the NUTS-2 level are not available for Slovenia, we attribute the country value to both regions.

TABLE 3.2: Data description

Variable name	Description	Time period	Source
Labor productivity	The ratio of the total Gross Value Added (GVA) over the total hours worked	Average (1993-2003)	ERD
Hours worked per employee	The average number of annual hours worked per employee	Average (1993-2003)	ERD
Share of GVA in services	The ratio of the GVA in service over the total GVA	Average (1993-2003)	ERD
Share of GVA in agriculture	The ratio of the GVA agriculture over the total GVA	Average (1993-2003)	ERD
Employment on the active population	The ratio of the number of employees (workplace-based measure) on the number of employed and the unemployed people (household-based measure), economically inactive	Average (1993-2003)	ERD
Compensation per employee	The sum of wages and salaries, and employers' social contributions, deflated to 2005 constant price	Average (1993-2003)	ERD
Population	The population in logarithm	Average (1993-2003)	ERD
EQI index	Citizen-based perception and experience with respect to corruption, quality and impartiality in terms of education, public health care and law enforcement	Average (1996-2003)	Charron et al., 2014
Trade openness	The ratio of exports plus imports over the GDP	Average (2000-2003)	PBL
Trade balance	The ratio of exports minus imports over the GDP	Average (2000-2003)	PBL
Share of 65+ population	The ratio of the population over 65 over the total population	2003	ERD
Share of foreigners	The ratio of the foreign resident population of working age over the total resident population of working age	2001	Eurostat

Notes: For the EQI index, the EU average is 0; negative value are below the EU average, positive value are above the EU average. In pre-treatment period the smallest EU value was -3.32 while the biggest value was 2.71.

3.6 Methodology

To estimate the effect of joining the euro for the eastern European area on the GDP per capita, we use the KB estimator proposed by Hazlett and Xu, 2018. This is a general reweighing approach to the causal inference which builds upon the SCM, developed by Abadie and Gardeazabal, 2003 and Abadie et al., 2010, enabling us to estimate the treatment effect in the presence of few treated units. The idea behind KB is that in a difference-in-differences setting with one or few treated units, it is possible to construct, transparently, a 'synthetic' counterfactual unit that can better mimic what would have happened to the units treated in the absence of treatment. The 'synthetic' unit is built as a weighted average of control units whose pre-treatment characteristics closely match that of treated units. Therefore, the treatment effect in each post-treatment period ($t > T_0$) is given by the difference between the observed outcomes for the treated regions and the 'synthetic' control unit. Considering the whole eastern euro area, the average treatment effect for each post-treatment period (ATT_t) is equal to:

$$\widehat{ATT_t} = \frac{1}{N_{tr}} \sum_{G_i=1} Y_{it} - \sum_{G_i=0} w_i Y_{it}, \quad T_0 < t \leq T,$$

where N_{tr} = number of treated (in our case the 9 regions that join the euro), G_i is the group indicator that is equal to 1 if the region i lies in the treated group, and equal to 0 if i lies in the control group, and Y_{it} is the outcome variable of region i at time t, w_i is the control weight. The w_i are chosen s.t.

$$\frac{1}{N_{tr}} \sum_{G_i=1} \phi(Y_{i,pre}) = \sum_{G_i=0} w_i \phi(Y_{i,pre}),$$

and $\sum_{G_i=0} w_i = 1$; $w_i > 0$ for all i in the control group. $Y_{i,pre}$ [21] must be made equal for the treated and control regions, not only in the average trajectory but also on the higher-order representation of the pre-treatment history $\phi(Y_{i,pre})$. This allows us to eliminate the bias in the ATT estimates, ensuring that the control regions that are more similar to the treated regions in their trajectories receive higher

[21] For the sake of brevity, $Y_{i,pre}$ includes pre-treatment outcomes as well as pre-treatment covariates.

weights[22]. To choose $\phi()$ and then determine weights, a kernel-based approach is used. The basis of this approach consists in kernels, i.e., functions that assess similarity for each covariate and pre-treatment outcome between unit i and each other unit. $\phi(Y_{i,pre})$ can be represented as simply K_i, or in matrix form Y^{pre} as K. K_i has the form $[k(Y_i, Y_1), k(Y_i, Y_2), ..., k(Y_i, Y_N)]$, where N are the number of observations and $k(Y_i, Y_j)$ is a function that measures similarity between unit i and unit j. Given that an exact balance on all N dimensions of K is typically infeasible, we seek an approximate balance. The basic idea is to minimize the (worst-case) bias due to this approximation: (1) take the eigenvectors of K based on singular value decomposition (SVD), and (2) achieve balance on the first P eigenvectors, leaving those whose eigenvalues rank $P+1$ to N unbalanced, where (3) the value of P is chosen to minimize the 'worst-case' bias that could arise due to remaining imbalances. As using this procedure makes it difficult to find a set of weights that reduce the imbalance between treated and control groups, it may be necessary, before reweighing, to subtract from the original outcome variable of each unit the average outcome in the pre-treatment period, ensuring mean zero outcomes in the pre-treatment period. While making feasible weights easier to find, this comes at the cost of an invariance assumption.

The heterogeneous estimated effect for each eastern euro region ($\widehat{\theta_{it}}$) is equal to

$$\widehat{\theta_{it}} = Y_{it} - \sum_{G_i=0} w_i Y_{it}, \quad T_0 < t \leq T.$$

The KB offers additional advantages over SCM by:

1. reducing user-discretion (it does not require one to specify which pre-treatment outcomes or covariates or their higher-order interactions to be matched on, thus minimizing the negative effects of research degrees of freedom);
2. accommodating for several treated units;

[22]Matching not only on the average but on all distribution of the trajectories is very important particularly when, for example, a control group that varies wildly around a flat line could be well mean balanced to a treated group that has all 'flat' trajectories. Yet, the treated and control groups would look very different on features such as variance or volatility. If these features later come to have a large directional impact on the outcome, this imbalance can generate bias.

3. achieving balance on the high-order 'trajectory' of pre-treatment outcomes rather than their period-wise average (KB procedure ensures that the weighted control group is similar to the treated with respect to average values before the treatment, but also for high order features, such as 'volatility', 'variance' or 'curviness').

3.7 Results

3.7.1 Results: the effect on the eastern euro area

Figure 3.4 shows the trends of the average GDP per capita in PPS of the eastern European countries that joined the euro (dark line) and its synthetic counterpart (dashed line), i.e., the weighted average GDP per capita in PPS of control units, based on the KB approach. The horizontal axis represents the time in years, while the vertical axis represents the GDP per capita in PPS. We consider 2004 as the beginning of treatment (grey vertical line), as it is the year in which the majority of treated countries entered ERM II (KB does not allow accommodating for different treatment years in a single run). However, when we analyze the heterogeneous effects, we use the different ERM II entrance years as 'treatment start', as shown in Figure 3.5. The 'synthetic' eastern euro area resembles the pre-treatment characteristics of the eastern euro area, suggesting that it is a valid counterfactual. Indeed, the pre-treatment fit observed between treated and the synthetic eastern euro area in Figure 3.4 is very good, and it is bolstered by the high degree of covariate balancing reported in Table 3.3[23]. This table displays the mean values between the treatment and control groups in the pre-treatment covariates before and after reweighing via KB. We find that the adoption of

[23]The perfect balance is not reached on all covariates, and in a few cases, the unbalanced controls are more similar than the kernel balanced controls. This happens because the synthetic unit is a weighted average of control units and KB procedure gives a weight to each control region. Then, the weights are estimated through an approximation procedure that ensures that any function of the pre-treatment outcomes (and covariates) in a large space of smooth functions will have equal means in the treated and control groups. Indeed, as it is hardly infeasible to have an exact balance on all N dimensions of K, where N represents the units and K a $N \times N$ matrix where each element represents how similar is each pair of units, the KB seeks an approximation balance on P dimensions. In this way, it is possible to minimize the worst-case bias and ensuring that the joint-distribution of covariates and pre-treatment outcomes is approximately balanced.

the euro brought about a positive effect on the whole period considered. However, after the onset of the financial crisis (the dashed vertical line), we observe a reduction of the eastern euro area's economic gain. In Table 3.4, one can observe the overall average treatment effect and the treatment effect at the middle of the crisis and in the last observed year for the eastern euro area and for every single region which joined the euro. This finding suggests that, in general, for the eastern euro area, the positive effects of being in a currency union outweighed the economic costs despite the time of crisis[24].

TABLE 3.3: Covariate balancing

	Treated	Unbalanced controls	Kernel balanced controls
Labor productivity	6.59	5.21	6.97
Annual hours worked per employee	2,083.14	1,979.20	2,073.87
Share of GVA in services	65.96%	58.70%	64.39%
Share of GVA in agriculture	4.43%	7.13%	3.61%
Employment on active population	88.64%	89.74%	94.47%
Compensation of employee (Millions of €)	5,240.29	3,438.37	4,800.45
Share of foreigners	4.19%	1.02%	1.63%
EQI index	-0.73	-0.88	-0.59
Trade openness	1.17	1.14	1.32
Trade balance	-0.06	-0.06	-0.02
Share of 65+ population	13.60%	14.21%	14.11%
Population (ln)	14.18	14.39	14.44

Notes: The columns represent the average value of the treated regions, control regions, and control region after a kernel balancing procedure for each covariate in the row.

[24] In Appendix C.3, we report an additional analysis concerning the employment (in logarithm terms). Differently to per capita GDP that has a positive, even if small, effect, employment does not seem to be impacted by the euro adoption.

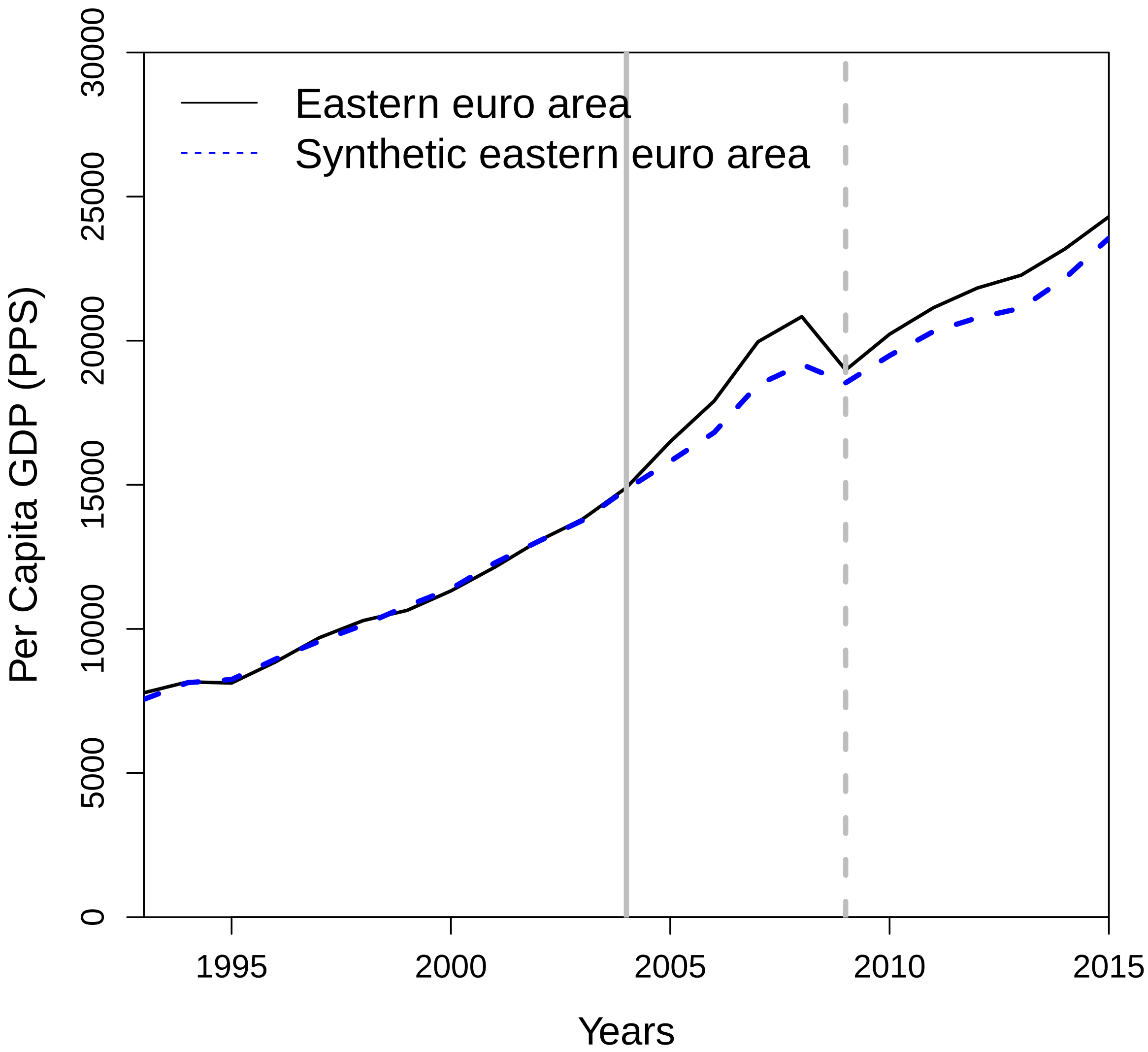


FIGURE 3.4: Trends in GDP per capita: eastern euro area and synthetic eastern euro area

TABLE 3.4: Treatment effects in different times

	ATT	TE 2009	TE 2015
Bratislava Region	€9,603.93	€8,928.43	€13,254.06
Western Slovakia	€2,571.21	€2,056.31	€2,558.72
Central Slovakia	€873.41	€741.46	€1,088.59
Eastern Slovakia	€184.50	€-214.28	€23.25
Latvia	€-920.73	€-2,161.55	€-1,176.67
Estonia	€-674.87	€-2,343.97	€-1,193.15
Lithuania	€1,560.03	€-278.79	€2,761.17
Eastern Slovenia	€-2,127.40	€-1,917.79	€-4,212.93
Western Slovenia	€-4,659.40	€-4,784.79	€-4,212.93
Eastern euro area	€910.23	€442.92	€741.36

Notes: The first column indicates the average treatment effect for the whole post-treatment period. The second and the third columns indicate the treatment effect for 2009 and 2015, respectively.

3.7.2 Results: the regional effects

It is difficult to argue that with the accession of eastern European countries to the euro area, the conditions for an OCA (homogeneity, i.e., economic similarities, or at least flexibility on the labor market) were satisfied for all regions. Therefore, we might expect that the treatment impact is not homogeneous across areas. So, despite the positive average impact, some regions might have been damaged by joining the euro area. To identify the impact heterogeneity, we analyze each treated NUTS-2 region.

Like the whole eastern euro area, all synthetic regions' per capita GDP very closely track the trajectories for the treated regions in the pre-treatment period, as we can observe in Figure 3.5. This suggests an accurate approximation.

In Table C.1 in Appendix, we report the KB weights of regions that contribute to synthetic. For example, the synthetic version Bratislava region, which is the second wealthiest region among all, is composed of 57.9% of Prague (CZ01), the wealthiest region, by 16.3% of Western Transdanubia (HU22), 13.8% of Mazowieckie (PL12), 12% of Central Hungary (HU10). These last three are among the wealthiest regions and with a very similar economic structure to the Bratislava region.

Figure 3.5 shows the per capita GDP and the counterfactual for every region.

After the beginning of the financial crisis, we observe a reduction of the positive impact of adopting the euro or an increased negative impact, which is temporary for some regions and permanent for others. Both Slovenian regions suffer from joining the euro area, with losses that increase after the crisis. On the contrary, Slovak regions suffer little from the crisis. Overall, the Slovakian region of Bratislava experienced an economic gain from joining the euro also during the crisis. Bratislava is the only 'core' region among the treated units, as it is the only urban region bordering on EU-15, and it is by far the wealthiest region.
Concerning the Baltic countries, while they entered ERM II between 2004 and 2005, they adopted the euro only between 2011 and 2015. Such a long time span might suggest that the euro had a more moderate impact on them than on countries that managed a quicker adoption. Although it took them a few years to meet all Maastricht conditions, the Baltic countries always satisfied the exchange rate stability criteria also in the crisis period. This choice led to an internal devaluation via austerity measures and nominal wage reduction to restore competitiveness and reorient their production to new markets (Kuokštis 2011). This was possible for the so-called 'Baltic flexibility,' allowing them to quickly recover in the early 2010s after being harshly hit by the Great Recession (Kahanec, Zimmermann, et al. 2016). However, there are differences between the three countries. According to Kuokštis, 2011, Latvia responded in a less flexible way to changes in economic conditions than Estonia and Lithuania and faced the most significant difficulties. Our findings confirm this: Latvia is the Baltic country that suffered the most from the onset of the crisis. Nevertheless, in the early 2010s, it quickly recovered most of the economic losses. Lithuania obtained a positive effect when entering the ERM II, then experienced a loss during the early crisis period, but after it quickly bounced back. Estonia did not gain or lose, except at the beginning of the Great Recession, where we observe a moderate loss.
It is likely that these outcomes have been amplified by the EU's political choice to focus on growth cores in response to the Great Recession (see Pike et al. 2016).

Overall, our results reinforce the importance of considering regions' heterogeneity. When there is no exchange rate risk, the regional economic and productive structure

is critical to enhancing growth and resilience to adverse shocks. Investigating the theoretical predictions from the regional perspective, we can discuss four main channels: the accession to large markets, the urbanization degree as a proxy of developed areas, the openness to trade, and the similarity of the business cycle.
Regions with better access to new markets, such as port cities and border regions, are assumed to profit from economic integration. In our case, four regions sharing their borders with early-adopter euro regions, but only two of them obtain gains. Concerning the urbanization degree, we can observe two urban regions (Bratislava and Latvia) and only one rural (Eastern Slovenia) region. Therefore, except for Latvia, where we already discuss the particular conditions, we can affirm that it is likely core and more developed regions attracted more investments, disadvantaging the least developed regions, as shown in Table 3.5. As economic integration reduces trade costs, doing business becomes more convenient, so regions with high openness to trade (e.g., Bratislava) are also the regions that benefit the most from the single currency, in line with McKinnon, 1963 prediction. On the contrary, as shown in Figure C.1 in Appendix, some of the regions with low openness to trade (mainly the Slovenian regions) experience substantial losses in terms of per capita GDP. Another issue involves the similarities of the business cycle. As a proxy for this, we considered the correlations between the growth rate of early-adopter euro regions and each treated region over the ten years before the treatment[25]. In this case, there seems to be no relationship between growth and business cycle synchronization, as shown in Figure C.2 in Appendix.
However, all these elements should be viewed as a whole, together with all dynamics that can play a role and considering the reaction to the adverse shocks, as the crisis. A deeper analysis of driver channels would help to understand the motivation beyond our results.

[25]For Estonia, we consider nine years before the treatment given the limited data availability.

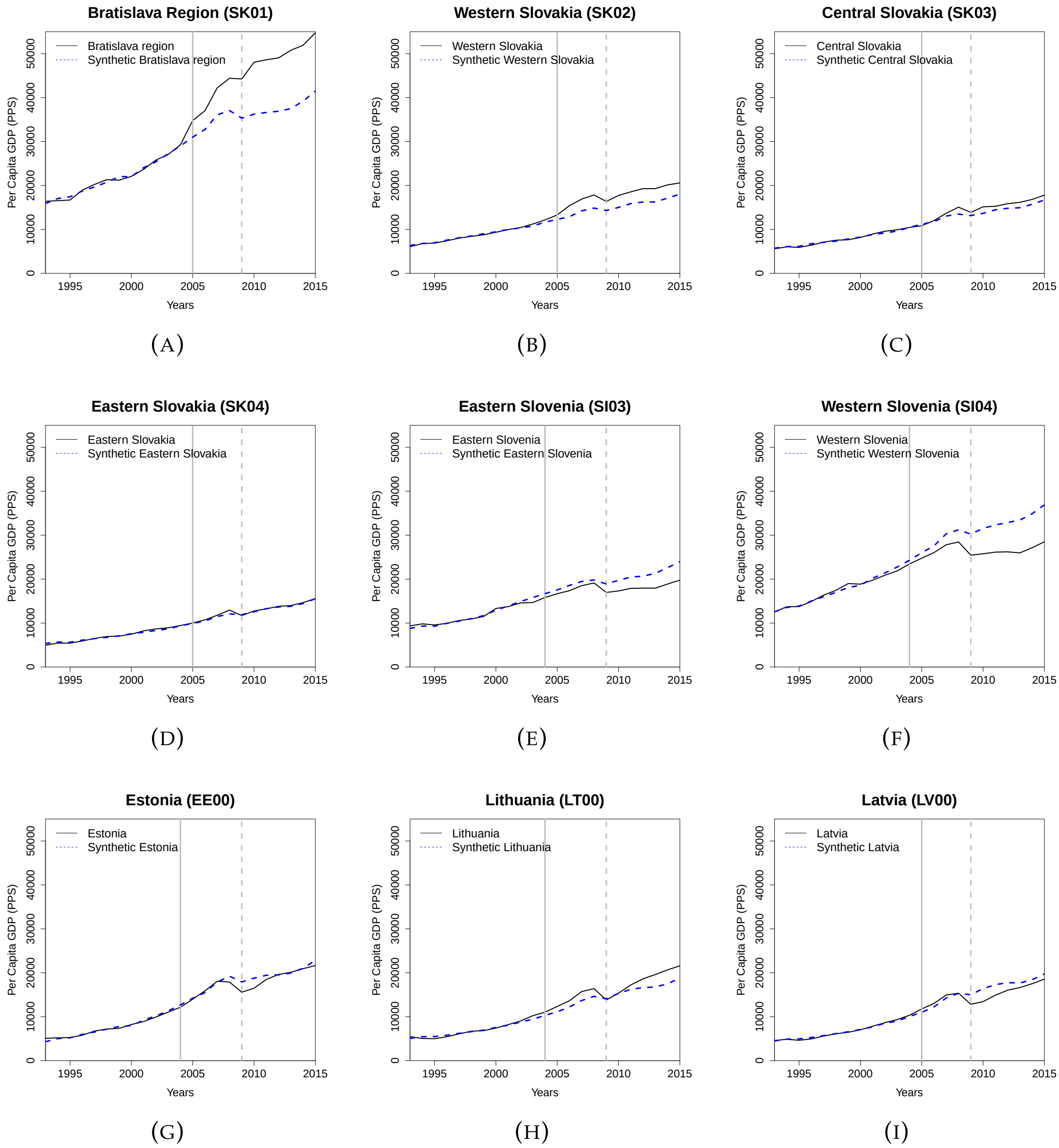


FIGURE 3.5: Trends in GDP per capita (NUTS-2 level)

TABLE 3.5: Eastern euro regions' characteristics

NUTS2	NAME	EURO BORDER	URBANIZATION
EE00	Estonia	-	Intermediate
LT00	Lithuania	-	Intermediate
LV00	Latvia	-	Urban
SI03	Eastern Slovenia	AT21, AT22	Rural
SI04	Western Slovenia	AT22, ITH4	Intermediate
SK01	Bratislava Region	AT11, AT12	Urban
SK02	Western Slovakia	AT12	Intermediate
SK03	Central Slovakia	-	Intermediate
SK04	Eastern Slovakia	-	Intermediate

Notes: Data on urbanization are taken from Jonard et al., 2009. The regions are classified in 3 classes (rural, intermediate, and urban) on the basis of the share of population living in rural communes or located in urban centers as developed in the OECD methodology.

3.8 Placebo in-space

Following Abadie et al., 2010, we run in-space placebo tests to evaluate the statistical significance of the estimates. The in-space placebo test reassigns the treatment (euro accession) artificially to every potential control region in the donor pool, i.e., regions not in the euro area, creating a distribution of placebo effects. If the treated region's trend dominates placebo distribution trends, there is a likely statistically significant effect. On the contrary, if sizable estimate effects on control regions are similar or larger, the statistical significance disappears. We repeat the process for each of the nine treated regions. Figure 3.6 depicts the gaps for treated (black line) and controls (grey lines). This test suggests that our estimates are statistically significant for the Bratislava region, Western Slovakia, the Slovenian regions, and Lithuania, as shown in Figure 3.5[26].

In Appendix C.4, we report an alternative statistical significance test (ratios between RMSPE post- and pre- euro adoption and the relative p-values) first proposed by Abadie et al., 2015. This test generally confirms the aforementioned results.

[26]There is an unusually large treatment effect for some control regions. This is a common situation in SCM literature, and it is due to an imperfect pre-treatment fit of the 'synthetic' placebo regions. The regions with a bad fit are usually removed because considered not useful to evaluate the statistical significance of the estimates. We exclude from the donor pool regions with a pre-treatment Mean Squared Prediction Error (MSPE) of more than 5 times the MSPE of each treated region, so regions for which the approach used is ill-suited.

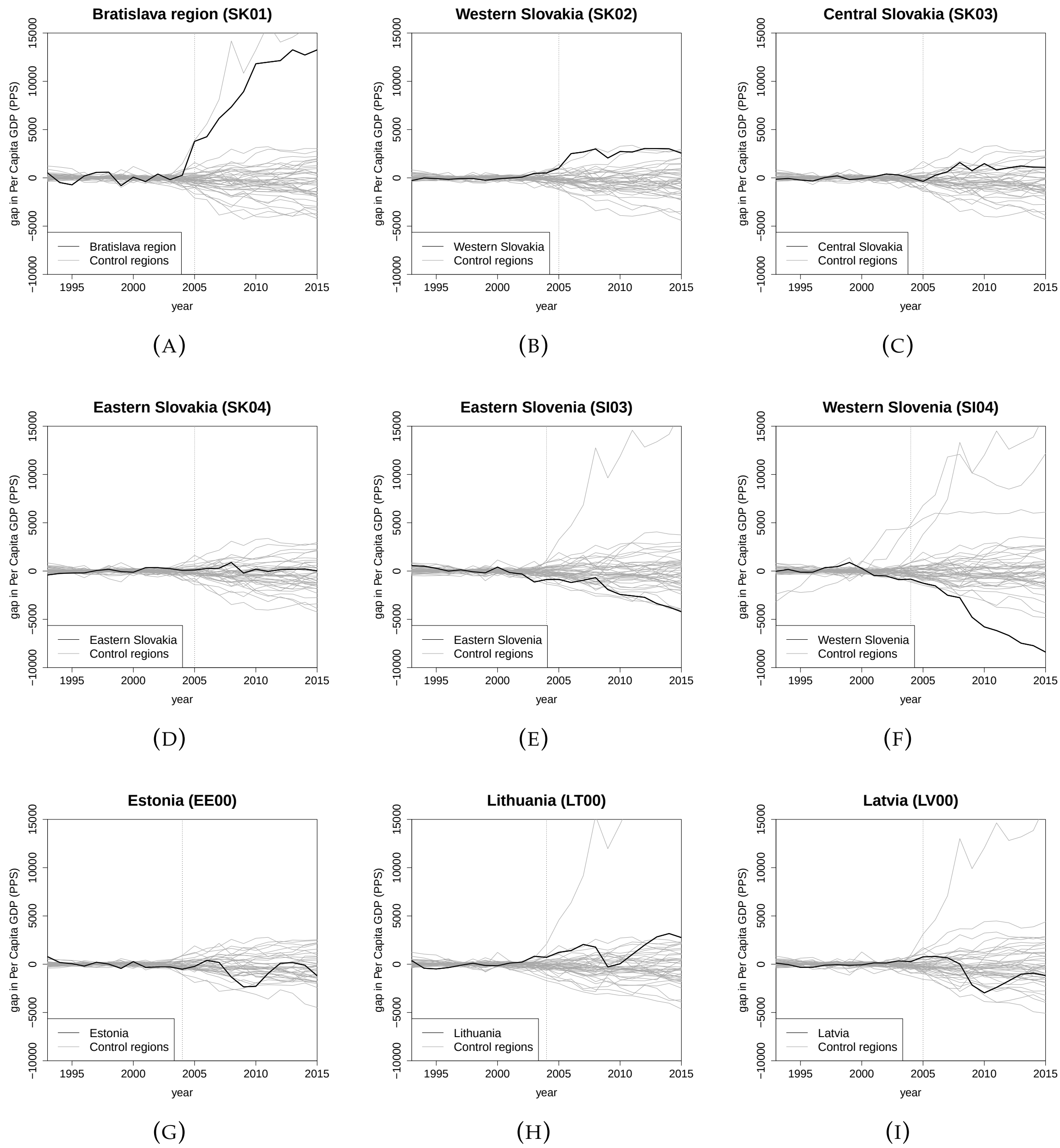


FIGURE 3.6: In-space placebo: gap in GDP per capita at NUTS-2 level.

Notes: In Panel (a) there are 43 regions plus Bratislava region; in panel (b) there are 40 regions plus Western Slovakia; in panel (c) there are 39 regions plus Central Slovakia; in panel (d) there are 45 regions plus Eastern Slovakia; in panel (e) there are 43 regions plus Eastern Slovenia; in panel (f) there are 43 regions plus Western Slovenia; in panel (g) there are 37 regions plus Estonia; in panel (h) there are 43 regions plus Lithuania; in panel (i) there are 42 regions plus Latvia.

3.9 Robustness checks

The sensitivity of the per capita GDP estimates was tested by changing:

1. *The donor pool*.
   We propose a leave-one-out analysis, i.e., we re-run the KB, excluding from the sample one-at-a-time each of the regions that contribute to the counterfactual. The findings are shown in Figure 3.7. It emerges that no particular donor region is driving our main findings. Only the results of Estonia and Western Slovenia seem to be less robust.
   We then restrict the donor pool of each treated region to regions having the same level of urbanization (rural, intermediate, or urban). The results are reported in Figure 3.8. The figure depicts the synthetic region (dashed blue line) as well as the synthetic region built with a restricted donor pool in terms of urbanization (dashed green line). The results are similar to the main analysis, except for the Bratislava region and Latvia, where the effects become even larger (even if with the opposite sign), for Slovenian regions where the effect is positive before the crisis, and for Estonia where it is positive for the entire post-treatment period[27].
   Lastly, as all of our treated regions joined the EU in 2004, we exclude from the donor pool the Bulgarian and Romanian regions, which joined the EU in 2007. The results corroborate our main findings, even though Eastern Slovenia has a smaller negative effect, and Latvia a positive effect, as shown in Figure 3.9.

2. *The algorithm to assess weights*.
   We use Mean Balancing (MB), a procedure developed by Hazlett and Xu, 2018 that seeks balance on the first P principal components of the characteristics, where P is chosen automatically by a method that minimizes the worst-case bias, and Synthetic Control Method (see Section 1.1 in the first Chapter). The findings shown in Figures C.4, C.5 , C.6, and C.7 in Appendix C.5 largely support the main analysis, both for the overall effect and the regional effects, except for Estonia, where the main analysis showed a negative effect during the beginning of the crisis. In contrast, the MB and SCM showed a positive effect.

[27] The results are slightly different from the main analysis, but the worst pre-treatment fit can justify this.

3. *The covariates*.
   We add tertiary education to the set of variables. The effects remain unchanged except for Estonia, as shown in Figure 3.8, where we observe the synthetic trends in the presence (dashed red line) and in the absence (dashed blue line) of the education variable[28].

[28] We do not add tertiary education covariate in the main analysis because Eurostat only releases the national data for Slovenia.

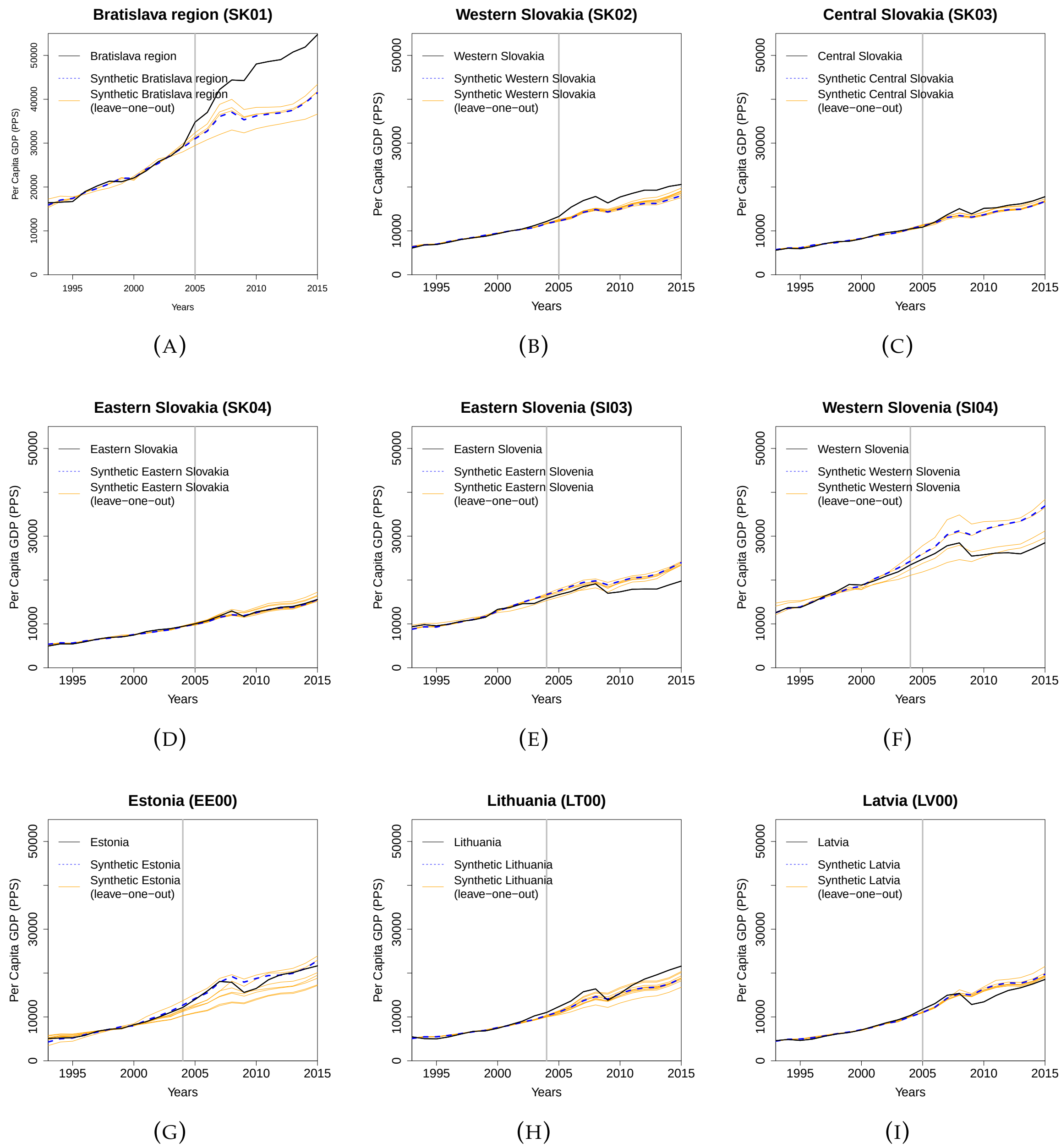


FIGURE 3.7: Leave-one-out procedure (NUTS-2 level)

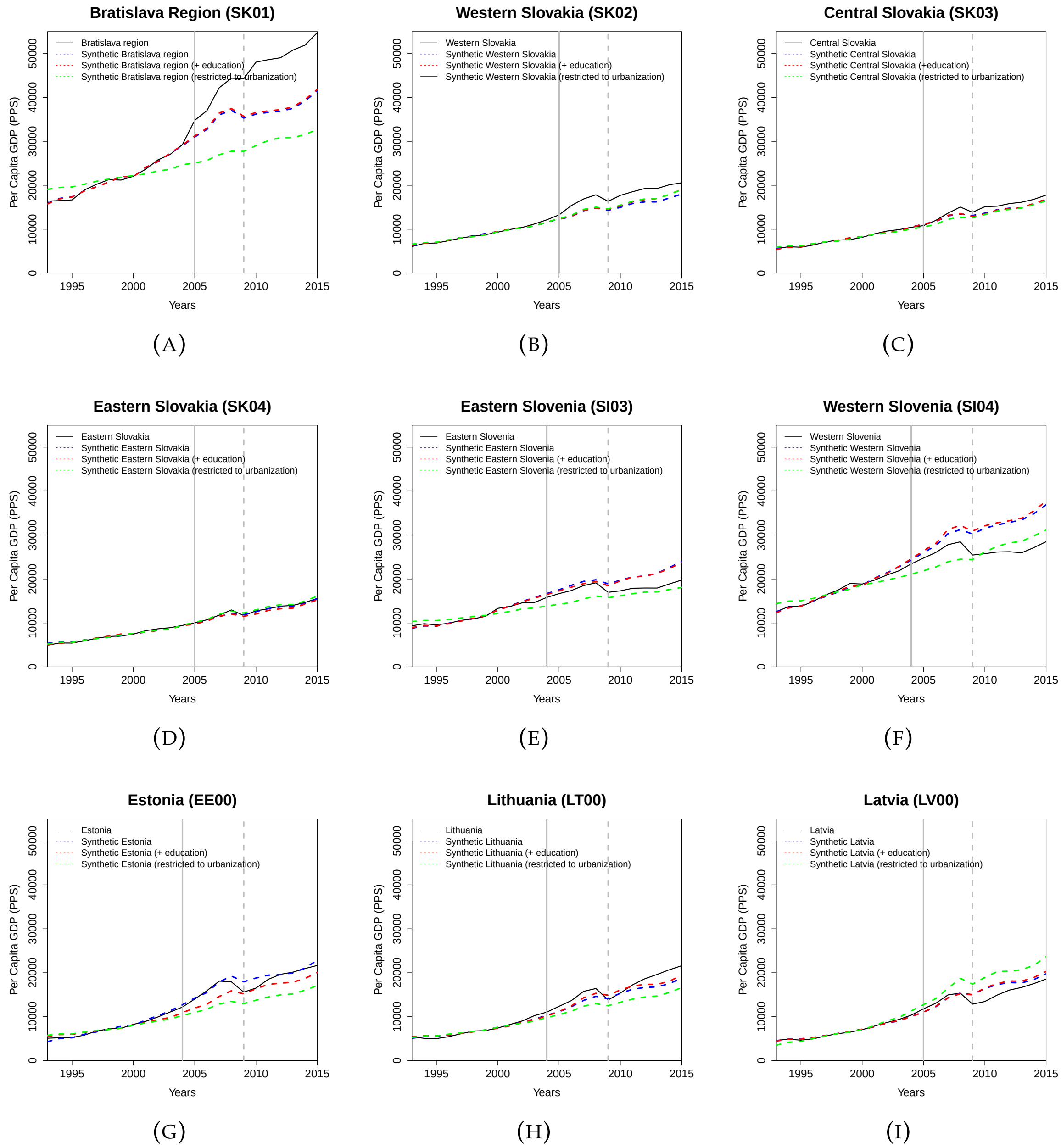


FIGURE 3.8: Robustness checks: added variable and restricted donor pool on urbanization degree

Notes: Data on education are taken from Eurostat. Eurostat issues data on tertiary education for every NUTS2 region in our dataset, except for two Slovenian regions. So, we attribute the national percentage of 15-64 people obtaining tertiary education to both regions.

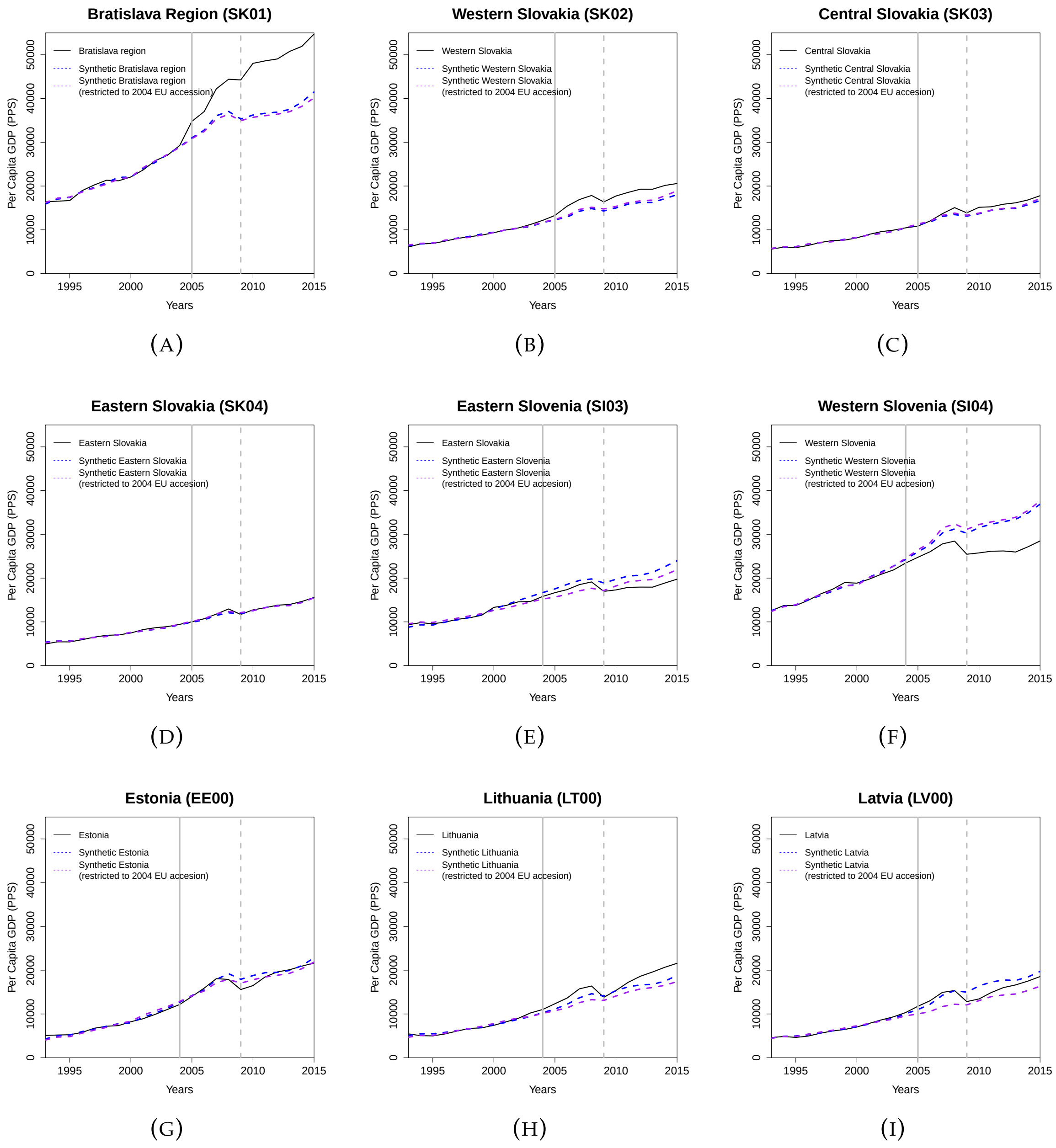


FIGURE 3.9: Robustness checks: restricted donor pool on 2004 EU accession regions

3.10 Conclusion

With the end of the Cold War and the collapse of the communist Eastern Bloc, several eastern European countries initiated an integration process with the rest of Europe, which culminated with the EU enlargement between 2004 and 2007 to 27 Member States. Simultaneously, some eastern European countries (Slovakia, Slovenia, and the Baltic countries) also decided to join the euro area. These countries entered the ERM II immediately before the Great Recession, so they could not use monetary policy to address the crisis. In this context, the crisis undoubtedly represented a considerable shock to this integration model (Becker et al. 2010). Stiglitz, 2017 argues that the shock caused by the 2007–08 financial collapse cast new doubts about the ability of the currency union to properly operate in the presence of regional economic diversities. Indeed, regions' different characteristics can determine a positive or negative effect of the euro on the economy, bringing winner and loser regions often inside the same country, and the overall net effect can be undetermined. In this case, do 'one-size-fits-all' policies represent the best possible solution? A common monetary policy could be sub-optimal, and appropriate differentiated policies could be more advantageous, particularly when a recession hits and the loss of monetary independence may prove to be costly.

In this chapter, we adopt a novel counterfactual approach to estimate the economic impact of adopting the euro for the latecomers and the individual regional effects of currency union participation. Our findings show, on average, a positive effect, which is, however, dampened by the Great Recession. Moreover, individual estimates exhibit highly heterogeneous returns. Given that the real convergence that helps optimality of the currency union was not fostered automatically by the monetary union for all regions (Coudert et al. 2020), it is necessary to revive the catching-up process. 'One-size-fits-all' policies, such as national fiscal policies, can be inefficient, and specific place-based policies that consider the economic characteristics of each region should be preferred. The solution of having greater mobility in wages to adjust asymmetric shocks within a country is often not feasible, and internal migration is costly. A more promising approach would be to support regional growth via customized regional and social policies aimed at enhancing welfare in the long run (Hallet 2004).

The strengthening of place-based policies has been pursued over time by the EU, which has increasingly used the European Structural and Cohesion Funds to facilitate regional integration processes and bear the Single Market costs for lagging regions. Our work results indicate that this is the right direction: monetary integration may require long convergence times for the weaker areas, and in the meantime, increase inequalities, which must be addressed with policies geared towards the resources and skills of the lagging areas. The growing acknowledgment of the region's role as a key spatial unit is important to strengthen competitiveness that could take action when the exchange rate and monetary policies could not.

Conclusion

The dissertation is part of the flourishing literature that estimates the causal effect of policy intervention in panel data settings with only one or a few treated and control units. In a context where many policy interventions occur at an aggregate level, the SCM literature assumes a focal role in the causal effect estimation.
The thesis analyzed the SCM features, its critical issues and presented alternative approaches for the counterfactual evaluation in the presence of a few units, shedding light on how recent methodological advances contributed to this literature. Mainly, in the first two chapters, it proposed a novel estimation approach that allows including units potentially affected directly or indirectly by an intervention in the donor pool and it showed how it works via an application. In the third chapter, it applied a recent methodological extension of the SCM, the KB, that improves on estimation accuracy and is applicable in a wider set of contexts.
The new methodology proposed in Chapter 1 tackles a common issue in contexts in which the intervention involves one or a few units: the trade-off between the 'right' comparison group and the no interference assumption (Abadie 2021). On the one hand, it is advisable to choose control units affected by the same regional economic shocks as the treated unit. This enables avoiding interpolation bias and estimating a synthetic unit that better represents what would have happened in case of no intervention. On the other hand, including control units affected by the same regional shocks, likely the most similar to the treated units, could provide biased estimates and consequently inaccurate policy recommendations. This issue concerns scenarios in which some of the units might be affected by spillover effects and scenarios in which there are multiple treated units and the control group is scarce and composed of units no so similar to the treated ones. The novel iSCM allows us to include these units safely in the donor pool and then eliminate post-intervention effects. Moreover,

it allows us to estimate the potential presence of spillover effects.
The iSCM can be easily applied thanks to its flexible nature and ease of implementation. Any synthetic control type estimation and inference can be adopted, therefore, also the KB, the recent re-weighting approach analyzed in the third chapter. Both approaches can be applied to evaluate micro or macro policy events. In fact, in the second chapter, we used iSCM to evaluate the economic impact of the German Reunification, and in the third chapter, we used the KB to estimate the regional economic impact of the euro adoption for eastern European regions. Despite splitting countries into regions, we are always in the presence of a few units, so the cutting-edge methodology used helped us improve the estimation accuracy.
To conclude, we remember that SCM and its extensions consist of a data-driven procedure that selects the units that contribute to the counterfactual. So, the credibility of the estimates depends on contextual and data requirements, both in time and space. We advise avoiding mechanical applications that ignore the context of the analysis or the features of the data. Indeed, although approaches for counterfactual evaluation in the presence of a few units, like those proposed in the thesis, can substantially contribute to estimating the causal effect of policy interventions or other events of interest, it is always crucial to take into account the practical requirements of the specific application to obtain robust causal estimate.

Appendix A

Appendix to Chapter 1

A.1 Non singularity

Let $\widehat{\Omega}_{ij}$ a generic element of $\widehat{\Omega}$. We have that

1. $\widehat{\Omega}_{ii} = 1, \ \forall i = 1, \ldots, m$ (the main diagonal elements are all one by definition).
2. $0 \leq |\widehat{\Omega}_{ij}| \leq 1$ (the non-diagonal elements include estimated weights).
3. $0 \leq \sum_i \widehat{\Omega}_{ij} \leq 1$. (the sum of the weights in a row cannot be bigger than one).
4. If $|\widehat{\Omega}_{ij}| = 1, \ j \neq i$, then all the non-diagonal elements on the same row are zero (if one of the weights equals one, all of the others must be zero).

As $\widehat{\Omega}$ is a square matrix, it is non-singular if, and only if, its determinant is different from zero, which can only be the case if none of the three conditions below are satisfied:

1. Either one of its rows or one of its columns only contains zeros.
2. Either two of its rows or two of its columns are proportional to each other.
3. Either one of its rows or one of its columns is a linear combination of at least two others.

The first and the second conditions are immediately ruled out by the fact that $\widehat{\Omega}$ always contains ones on its main diagonal and all its other elements are smaller than 1 in absolute value. The third conditions can only occur if either $\widehat{\Omega}_{ij} = \widehat{\Omega}_{ji} = -1, \ j \neq i$ or if in every single row we have $\sum_i \widehat{\Omega}_{ij} = 0$.

A.2 Two additional units potentially affected

In the case of 2 potentially affected units ($m = 2$), $j = 2$, and $j = 3$, the system of equation is equal to:

$$\begin{cases} \widehat{\theta}_t = \theta_t - \widehat{w}_2\gamma_{2t} - \widehat{w}_3\gamma_{3t} \\ \widehat{\gamma}_{2t} = -\widehat{l}_1^2\theta_t + \gamma_{2t} - \widehat{l}_3^2\gamma_{3t} \\ \widehat{\gamma}_{3t} = -\widehat{l}_1^3\theta_t - \widehat{l}_2^3\gamma_{2t} + \gamma_{3t} \end{cases} \tag{A.1}$$

So, we have a (3×3) matrix of weights $\widehat{\Omega}$, a (3×1) vector of estimated effects with SCM $\widehat{\beta_t}$ and a (3×1) vector of unknown parameters ϑ_t.

$$\widehat{\beta_t} = \begin{pmatrix} \widehat{\theta}_t \\ \widehat{\gamma}_{2t} \\ \widehat{\gamma}_{3t} \end{pmatrix} \qquad \widehat{\Omega} = \begin{pmatrix} 1 & -\widehat{w}_2 & -\widehat{w}_3 \\ -\widehat{l}_1^2 & 1 & -\widehat{l}_3^2 \\ -\widehat{l}_1^3 & -\widehat{l}_2^3 & 1 \end{pmatrix} \qquad \vartheta_t = \begin{pmatrix} \theta_t \\ \gamma_{2t} \\ \gamma_{3t} \end{pmatrix} \tag{A.2}$$

To solve with Cramer we have to find $\det(\widehat{\Omega})$, $\det(\widehat{\Omega}_{1,t})$, $\det(\widehat{\Omega}_{2,t})$ and $\det(\widehat{\Omega}_{3,t})$, applying Sarrus' rule.

$$det(\widehat{\Omega}) = \begin{vmatrix} 1 & -\widehat{w}_2 & -\widehat{w}_3 \\ -\widehat{l}_1^2 & 1 & -\widehat{l}_3^2 \\ -\widehat{l}_1^3 & -\widehat{l}_2^3 & 1 \end{vmatrix} = 1 - \widehat{w}_2\widehat{l}_3^2\widehat{l}_1^3 - \widehat{w}_3\widehat{l}_1^2\widehat{l}_2^3 - \widehat{w}_3\widehat{l}_1^3 - \widehat{l}_3^2\widehat{l}_2^3 - \widehat{w}_2\widehat{l}_1^2 \tag{A.3}$$

$$det(\widehat{\Omega}_1, t) = \begin{vmatrix} \widehat{\theta}_t & -\widehat{w}_2 & -\widehat{w}_3 \\ \widehat{\gamma}_{2t} & 1 & -\widehat{l}_3^2 \\ \widehat{\gamma}_{3t} & -\widehat{l}_2^3 & 1 \end{vmatrix} = \widehat{\theta}_t + \widehat{w}_2\widehat{l}_3^2 + \widehat{w}_3\widehat{l}_2^3\widehat{\gamma}_{2t} + \widehat{w}_3\widehat{\gamma}_{3t} - \widehat{l}_3^2\widehat{l}_2^3\widehat{\theta}_t + \widehat{w}_2\widehat{\gamma}_{2t} \tag{A.4}$$

$$det(\widehat{\Omega}_2, t) = \begin{vmatrix} 1 & \widehat{\theta}_t & -\widehat{w}_3 \\ -\widehat{l}_1^2 & \widehat{\gamma}_{2t} & -\widehat{l}_3^2 \\ -\widehat{l}_1^3 & \widehat{\gamma}_{3t} & 1 \end{vmatrix} = \widehat{\gamma}_{2t} + \widehat{l}_3^2\widehat{l}_1^3\widehat{\theta}_t + \widehat{w}_3\widehat{l}_1^2\widehat{\gamma}_{3t} - \widehat{w}_3\widehat{l}_1^3\widehat{\gamma}_{2t} + \widehat{l}_3^2\widehat{\gamma}_{3t} + \widehat{l}_1^2\widehat{\theta}_t \tag{A.5}$$

$$det(\widehat{\Omega}_3, t) = \begin{vmatrix} 1 & -\widehat{w}_2 & \widehat{\theta}_t \\ -\widehat{l}_1^2 & 1 & \widehat{\gamma}_{2t} \\ -\widehat{l}_1^3 & -\widehat{l}_2^3 & \widehat{\gamma}_{3t} \end{vmatrix} = \widehat{\gamma}_{3t} + \widehat{w}_2\widehat{l}_1^3\widehat{\gamma}_{2t} + \widehat{l}_1^2\widehat{l}_2^3\widehat{\theta}_t + \widehat{l}_1^3\widehat{\theta}_t + \widehat{l}_2^3\widehat{\gamma}_{2t} - \widehat{w}_2\widehat{l}_1^2\widehat{\gamma}_{3t} \tag{A.6}$$

Finally,

$$\widehat{\theta}_t^{iSCM} = \frac{\widehat{\theta}_t + \widehat{w}_2\widehat{l}_3^2 + \widehat{w}_3\widehat{l}_2^3\widehat{\gamma}_{2t} + \widehat{w}_3\widehat{\gamma}_{3t} - \widehat{l}_3^2\widehat{l}_2^3\widehat{\theta}_t + \widehat{w}_2\widehat{\gamma}_{2t}}{1 - \widehat{w}_2\widehat{l}_3^2\widehat{l}_1^3 - \widehat{w}_3\widehat{l}_1^2\widehat{l}_2^3 - \widehat{w}_3\widehat{l}_1^3 - \widehat{l}_3^2\widehat{l}_2^3 - \widehat{w}_2\widehat{l}_1^2} \tag{A.7}$$

$$\widehat{\gamma}_{2t}^{iSCM} = \frac{\widehat{\gamma}_{2t} + \widehat{l}_3^2\widehat{l}_1^3\widehat{\theta}_t + \widehat{w}_3\widehat{l}_1^2\widehat{\gamma}_{3t} - \widehat{w}_3\widehat{l}_1^3\widehat{\gamma}_{2t} + \widehat{l}_3^2\widehat{\gamma}_{3t} + \widehat{l}_1^2\widehat{\theta}_t}{1 - \widehat{w}_2\widehat{l}_3^2\widehat{l}_1^3 - \widehat{w}_3\widehat{l}_1^2\widehat{l}_2^3 - \widehat{w}_3\widehat{l}_1^3 - \widehat{l}_3^2\widehat{l}_2^3 - \widehat{w}_2\widehat{l}_1^2} \tag{A.8}$$

$$\widehat{\gamma}_{3t}^{iSCM} = \frac{\widehat{\gamma}_{3t} + \widehat{w}_2\widehat{l}_1^3\widehat{\gamma}_{2t} + \widehat{l}_1^2\widehat{l}_2^3\widehat{\theta}_t + \widehat{l}_1^3\widehat{\theta}_t + \widehat{l}_2^3\widehat{\gamma}_{2t} - \widehat{w}_2\widehat{l}_1^2\widehat{\gamma}_{3t}}{1 - \widehat{w}_2\widehat{l}_3^2\widehat{l}_1^3 - \widehat{w}_3\widehat{l}_1^2\widehat{l}_2^3 - \widehat{w}_3\widehat{l}_1^3 - \widehat{l}_3^2\widehat{l}_2^3 - \widehat{w}_2\widehat{l}_1^2} \tag{A.9}$$

In case of more than 2 spillover units, we can find the determinants through Laplace's rule.

Appendix B

Appendix to Chapter 2

B.1 The iSCM without including West Germany in Austria's donor pool

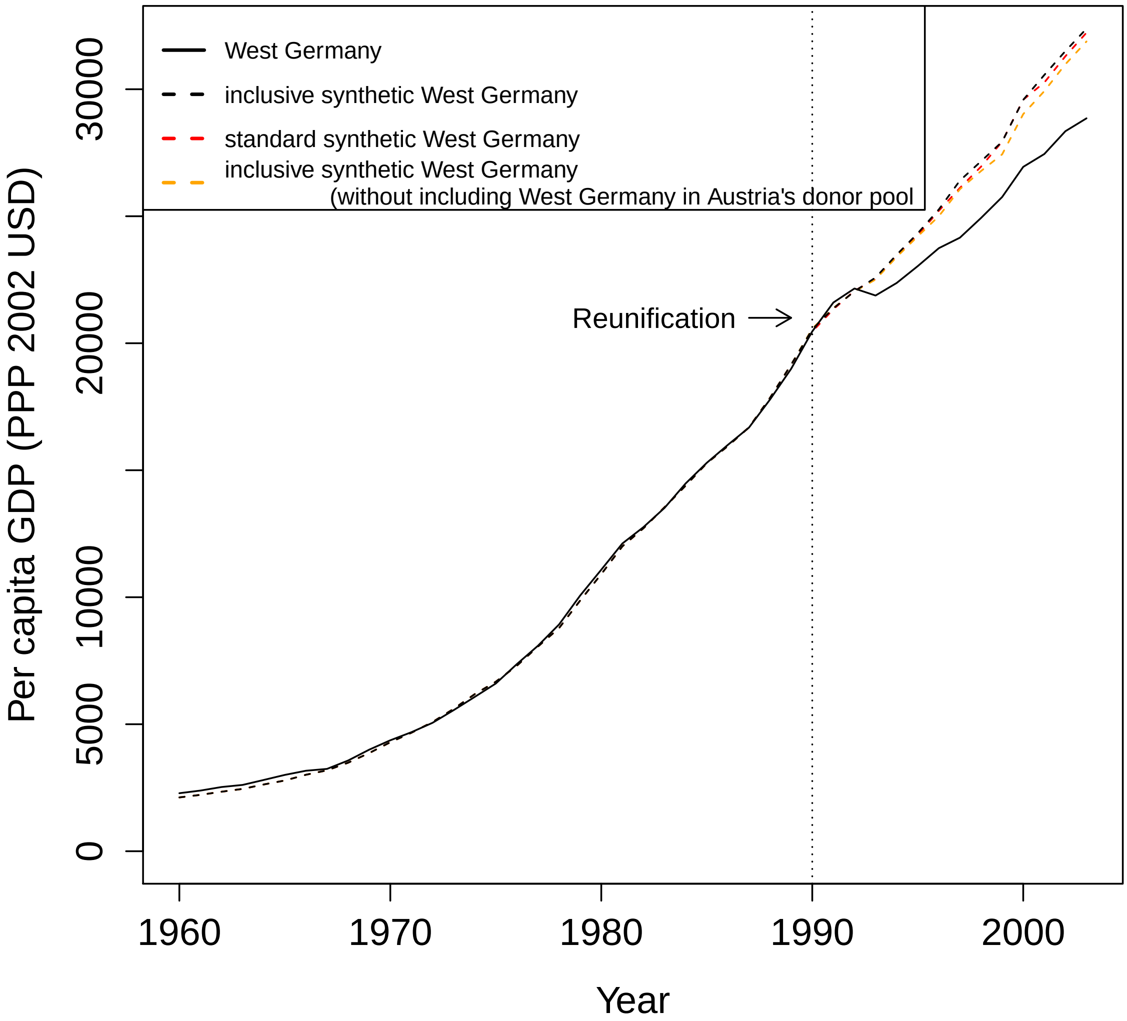


FIGURE B.1: Trends in per capita GDP: West Germany and synthetic West Germany versions

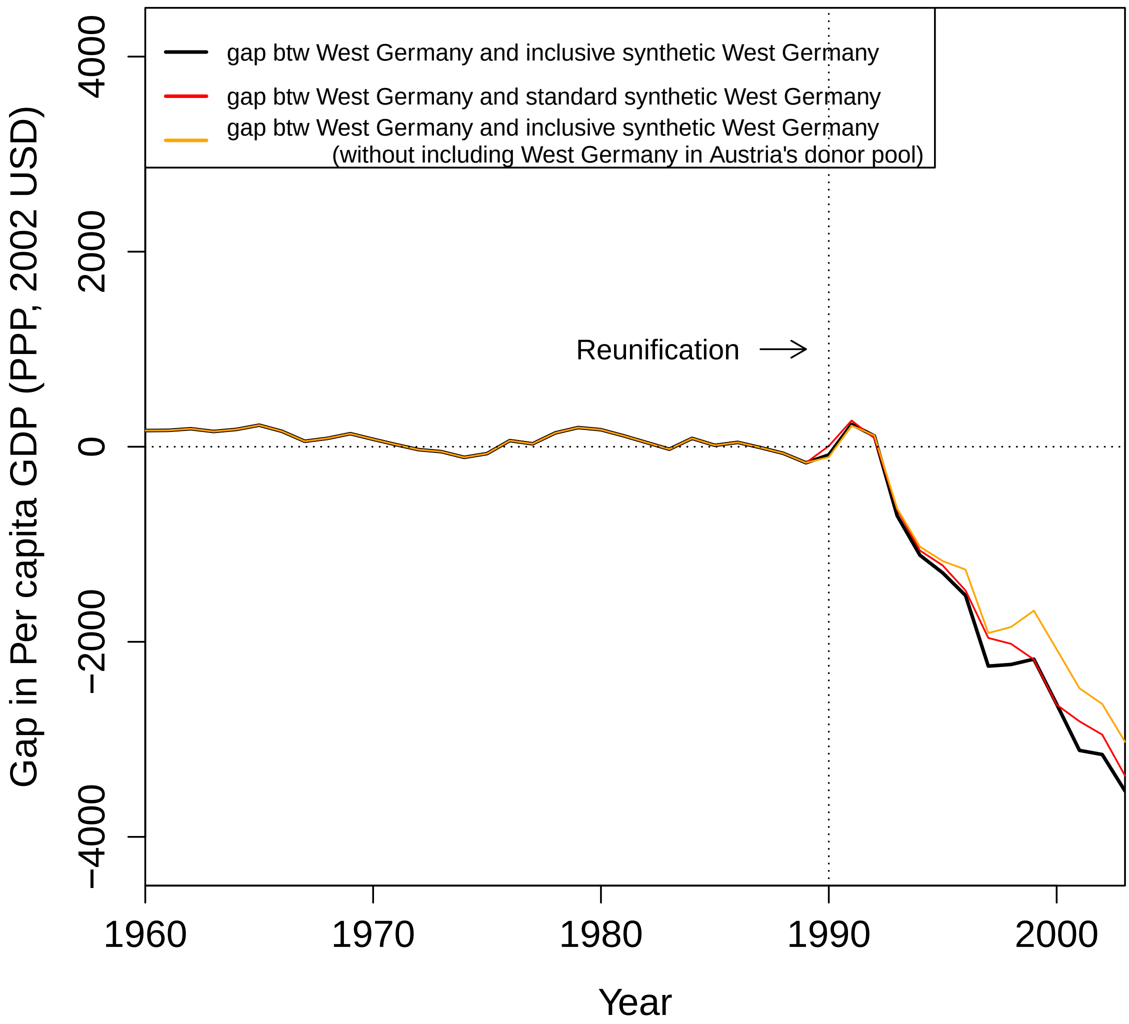


FIGURE B.2: Estimated effects on West Germany

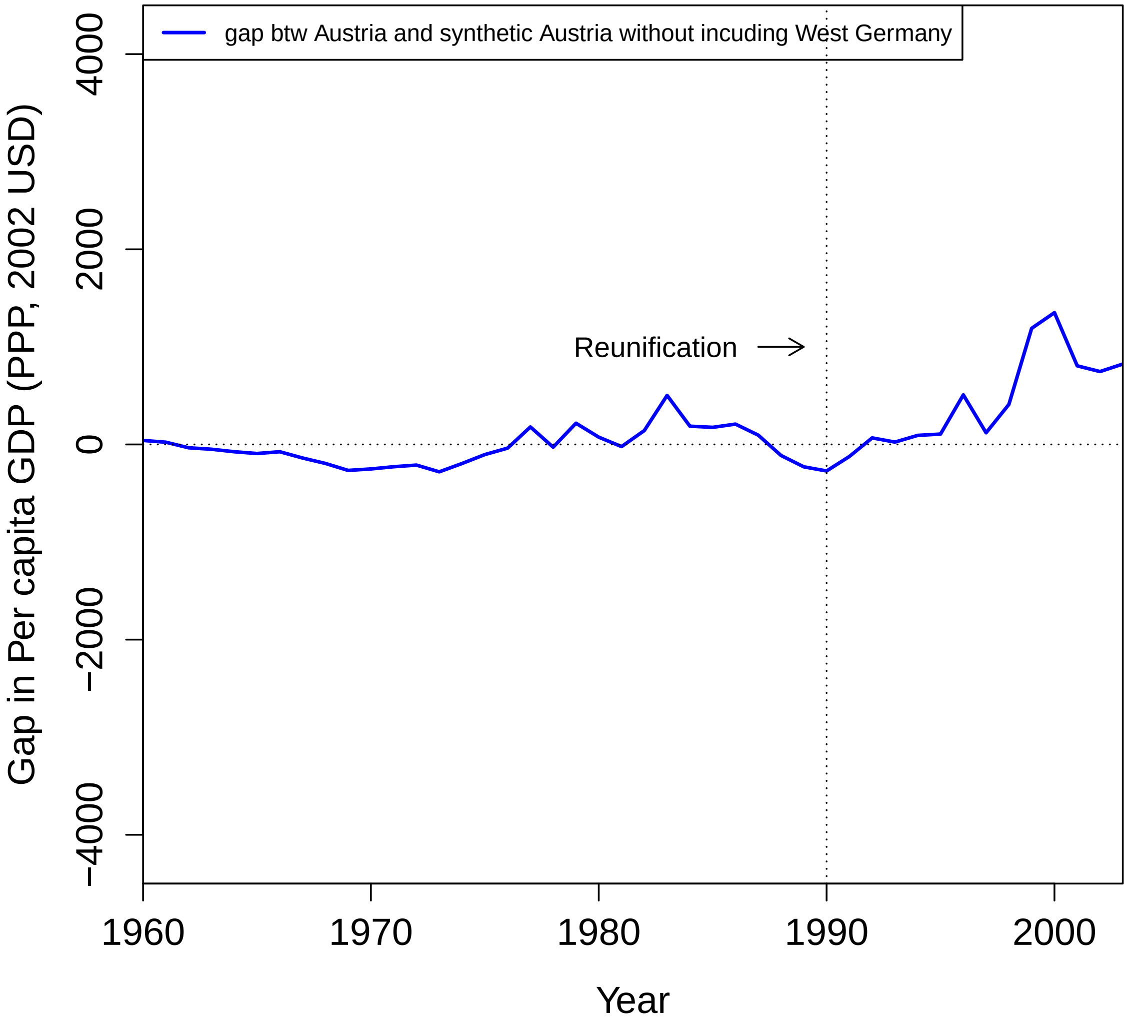


FIGURE B.3: Estimated effects on Austria

B.2 Robustness checks: three spillover effects

TABLE B.1: Pre-reunification RMSPE: standard and restricted version

	Standard SCM RMSPE	'Restricted' SCM RMSPE
West Germany	119.07	286.72
Austria	191.41	179.68
The Netherlands	331.58	397.95
Switzerland	1173.54	1190.37

TABLE B.2: Economic growth predictors before German Reunification: bias between observed country and synthetic country for standard and 'restricted' versions

	Bias West Germany	'Restricted' bias West Germany	Bias Austria	'Restricted' bias Austria	Bias Netherlands	'Restricted' bias Netherlands	Bias Switzerland	'Restricted' bias Switzerland
GDP per capita	4.26	0.96	0.88	29.90	354.32	650.03	1254.02	1254.02
Trade openness	0.14	24.98	0.00	0.00	0.22	0.01	52.25	52.25
Inflation rate	0.91	0.98	0.21	1.33	1.63	2.19	1.33	1.33
Industry share	0.15	0.20	0.00	0.75	1.09	0.13	1.27	1.27
Schooling	0.27	6.37	9.26	15.70	1.85	6.06	6.20	6.20
Investment rate	0.02	0.76	0.00	0.19	1.61	0.32	8.59	8.59

Notes: The bias for Switzerland are equal both in standard and in 'restricted' version because synthetic Switzerland is never composed of West Germany, Austria, and the Netherlands.

B.3 Robustness checks: a different algorithm

TABLE B.3: KB weights for West Germany and Austria

Country	Synthetic West Germany (KB weights)	Synthetic Austria (KB weights)
West Germany	-	0.25
Austria	0.79	-
Australia	0	0
Belgium	0	0.18
Denmark	0	0
France	0	0.07
Greece	0	0
Italy	0	0
Japan	0	0
Netherlands	0	0.13
New Zealand	0	0
Norway	0	0.37
Portugal	0	0
Spain	0	0
Switzerland	0.11	0
UK	0	0
USA	0	0

TABLE B.4: Economic growth predictors before German Reunification: KB West Germany and 'restricted' KB West Germany

	West Germany	KB West Germany	'Restricted' KB West Germany	Bias	'Restricted' Bias
GDP per capita (1980-1989)	14434.00	14242.20	13920.77	191.80	513.23
Trade openness	51.13	63.74	30.13	12.61	21.00
Inflation rate	3.83	5.04	8.71	1.21	4.88
Industry share	39.49	36.97	34.36	2.52	5.13
Schooling	53.70	52.47	48.56	1.23	5.14
Investment rate 1970	0.33	0.31	0.30	0.02	0.03
Investment rate 1980	27.02	26.68	28.00	0.34	0.98

TABLE B.5: Economic growth predictors before German Reunification: synthetic Austria and restricted synthetic Austria

	Austria	KB Austria	'Restricted' KB Austria	Bias	'Restricted' Bias
GDP per capita (1980-1989)	13518.18	13439.44	13018.34	78.74	499.85
Trade openness	68.95	78.12	68.08	9.17	0.87
Inflation rate	5.00	6.34	6.63	1.34	1.63
Industry share	38.00	37.10	36.41	0.91	1.59
Schooling	53.48	40.52	41.91	12.96	11.57
Investment rate	26.64	27.14	28.01	0.50	1.37

Appendix C

Appendix to Chapter 3

C.1 Kernel balancing weights

TABLE C.1: Bratislava region

NUTS-2 Code	Denomination	Weight
CZ01	Prague	0.58
HU22	Western Transdanubia	0.16
PL12	Mazowieckie	0.14
HU10	Central Hungary	0.12

We only report regions that contribute with weights greater than 0.009.

TABLE C.2: Western Slovakia

NUTS-2 Code	Denomination	Weight
PL33	Świętokrzyskie	0.30
CZ08	Moravian-Silesian	0.25
PL11	Łódzkie	0.17
PL34	Podlaskie	0.10
CZ05	Northeast	0.09
CZ07	Central Moravia	0.06
PL61	Kujawsko-Pomorskie	0.02
PL32	Podkarpackie	0.01

We only report regions that contribute with weights greater than 0.009.

TABLE C.3: Central Slovakia

NUTS-2 Code	Denomination	Weight
PL34	Podlaskie	0.23
CZ08	Moravian-Silesian	0.20
CZ04	Northwest	0.19
PL42	Zachodniopomorskie	0.10
PL32	Podkarpackie	0.09
CZ07	Central Moravia	0.05
PL43	Lubuskie	0.04
PL63	Pomorskie	0.04
CZ01	Prague	0.02

We only report regions that contribute with weights greater than 0.009.

TABLE C.4: Eastern Slovakia

NUTS-2 Code	Denomination	Weight
PL62	Warmińsko-Mazurskie	0.34
PL42	Zachodniopomorskie	0.26
CZ04	Northwest	0.17
HU31	Northern Hungary	0.08
PL22	Śląskie	0.08
HU10	Central Hungary	0.02
PL41	Wielkopolskie 0.02	
RO32	Bucureşti - Ilfov	0.02

We only report regions that contribute with weights greater than 0.009.

TABLE C.5: Eastern Slovenia

NUTS-2 Code	Denomination	Weight
CZ03	Southwest	0.31
HU22	Western Transdanubia	0.28
HU10	Central Hungary	0.21
HU21	Central Transdanubia	0.10
CZ01	Prague	0.05
CZ02	Central Bohemia	0.05

We only report regions that contribute with weights greater than 0.009.

TABLE C.6: Western Slovenia

NUTS-2 Code	Denomination	Weight
CZ01	Prague	0.37
PL12	Mazowieckie	0.36
HU10	Central Hungary	0.16
HU22	Western Transdanubia	0.12

We only report regions that contribute with weights greater than 0.009.

TABLE C.7: Estonia

NUTS-2 Code	Denomination	Weight
PL62	Warmińsko-Mazurskie	0.32
CZ01	Prague	0.29
HU31	Northern Hungary	0.14
HU10	Central Hungary	0.10
RO32	Bucureşti - Ilfov	0.10
BG41	Southwestern Bulgaria	0.04
PL12	Mazowieckie	0.01

We only report regions that contribute with weights greater than 0.009.

TABLE C.8: Lithuania

NUTS-2 Code	Denomination	Weight
PL21	Małopolskie	0.30
BG41	Southwestern Bulgaria	0.25
HU21	Central Transdanubia	0.14
RO42	Vest	0.13
PL12	Mazowieckie	0.05
PL11	Łódzkie	0.04
HU22	Western Transdanubia	0.03
BG42	Southern Central Bulgaria	0.02
HU10	Central Hungary	0.01
PL51	Dolnośląskie	0.01

We only report regions that contribute with weights greater than 0.009.

TABLE C.9: Latvia

NUTS-2 Code	Denomination	Weight
BG41	Southwestern Bulgaria	0.48
PL12	Mazowieckie	0.12
PL33	Świętokrzyskie	0.11
PL22	Śląskie	0.10
PL52	Opolskie	0.09
PL34	Podlaskie	0.05
PL51	Dolnośląskie	0.03

We only report regions that contribute with weights greater than 0.009.

C.2 Euro effects' potential channels

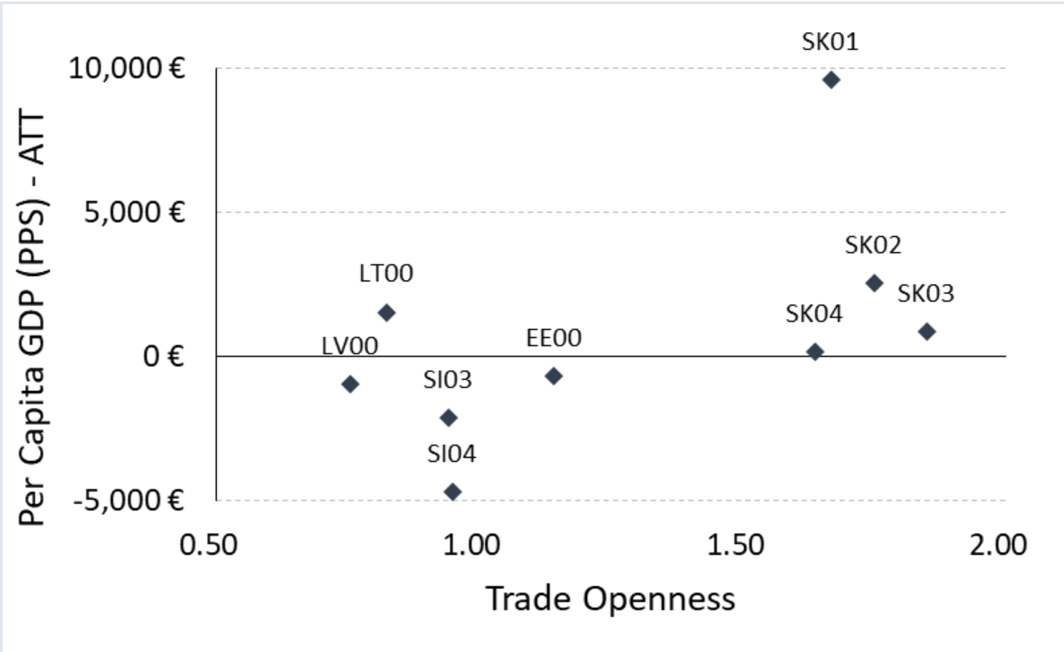


FIGURE C.1: Trade openness in eastern euro regions in 2003

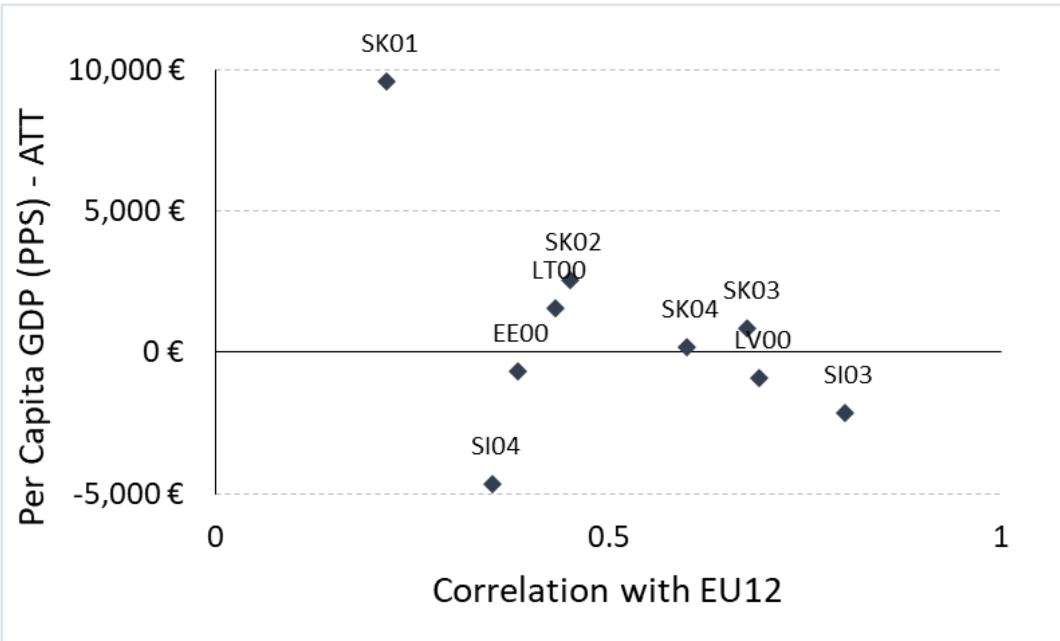


FIGURE C.2: Correlation between the ten-year growth rates (early-adopters euro region with treated regions) before euro treatment

C.3 Employment on eastern euro area

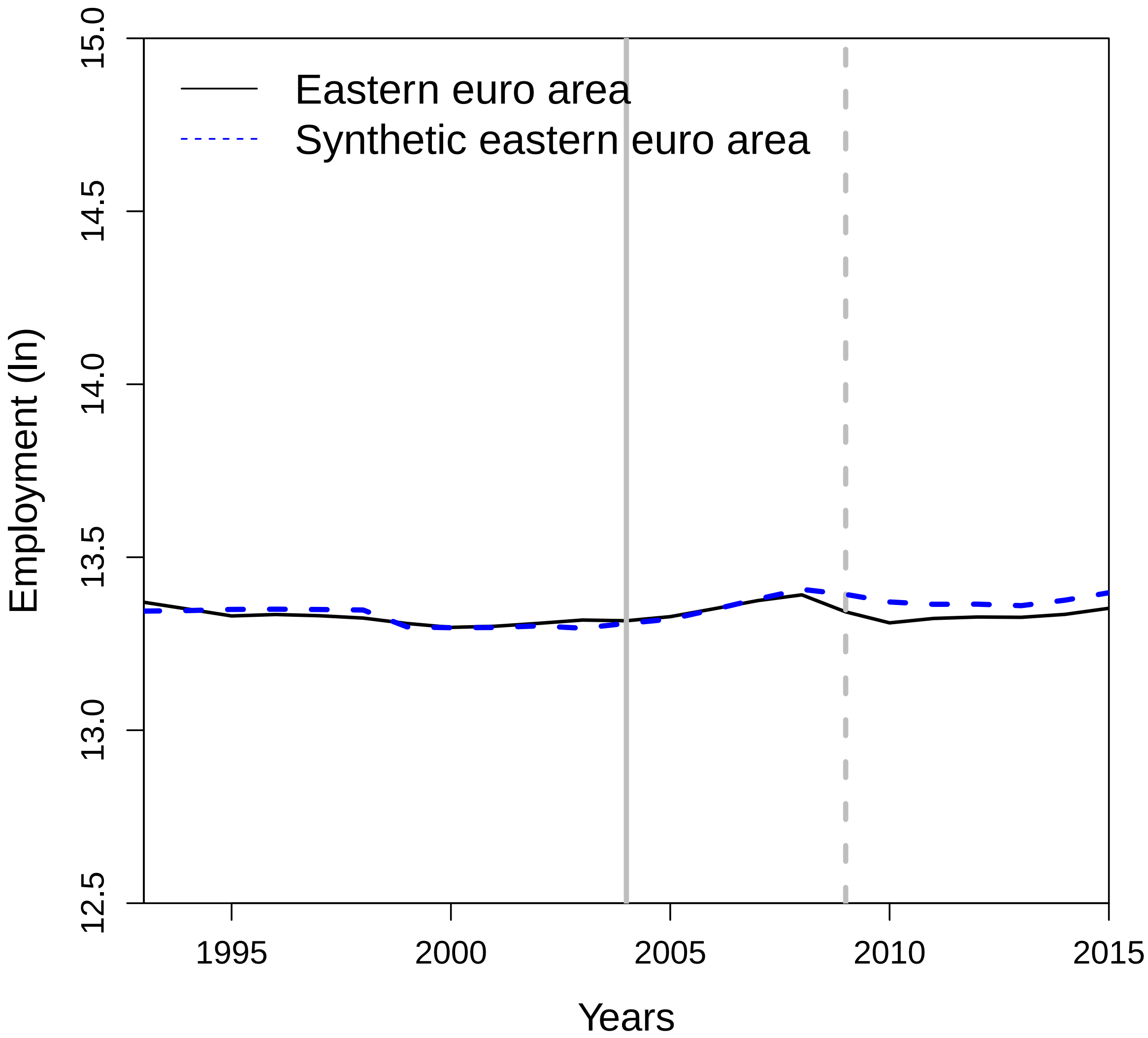


FIGURE C.3: Trends in employment (NUTS-2 level)

C.4 RMSPE

We follow Abadie et al., 2015 and compare the ratios between the post-treatment RMSPE and the pre-treatment RMSPE, separately for each region treated. The RMSPE measures the magnitude of the gap between the treated and 'synthetic' unit. In case of significant statistical impact, we expect a large numerator, i.e., a large gap in the post-treatment, and a small denominator, i.e., an almost perfect fit in the pre-treatment, for the treated. On the contrary, we do not expect any effect on the control regions, i.e., the ratio's small value. This means that the effect is statistically significant if the treated RMSPE ratio is larger than the distribution of the ratios for the controls. Table C.10 shows the RMSPE ratios and the associated p-values. The smallest p-values ($\leq$ 0.15) are observed for Western Slovenia, the Bratislava region, and Western Slovakia.

TABLE C.10: Post-treatment RMSPE/Pre-treatment RMSPE and p-values

	EE00	LT00	LV00	SI03	SI04	SK01	SK02	SK03	SK04
p-value	0.80	0.46	0.30	0.43	0.15	0.15	0.13	0.48	0.95
TR	3.37	5.13	7.93	5.36	11.22	9.29	7.63	4.71	1.46
BG31	4.38	4.11	4.96	4.67	4.03	4.18	3.52	3.51	3.57
BG32	12.67	13.89	9.73	12.15	11.43	8.83	8.87	8.85	8.86
BG33	5.69	5.76	4.95	5.68	2.29	2.97	5.30	5.28	5.26
BG34	2.44	2.58	2.50	2.51	2.47	3.15	2.78	2.84	2.80
BG41	3.85	4.07	9.98	2.62	2.48	3.10	2.51	2.55	2.54
BG42	3.94	3.90	8.28	3.81	3.96	4.43	7.44	7.65	7.96
CZ01	5.10	4.18	3.87	4.38	5.45	3.70	2.98	3.30	3.30
CZ02	3.82	6.97	4.00	7.19	4.31	2.66	2.56	2.60	2.55
CZ03	12.72	3.10	2.53	3.46	2.89	2.50	1.46	2.45	2.39
CZ04	1.35	5.03	7.86	5.59	7.34	5.47	5.51	5.47	5.31
CZ05	6.88	4.30	7.15	3.96	4.51	6.73	5.00	8.12	7.74
CZ06	10.74	6.87	12.72	10.85	10.63	13.17	6.85	13.87	13.90
CZ07	9.45	8.87	8.26	9.01	9.88	8.60	8.31	8.10	8.02
CZ08	10.90	11.01	5.83	11.95	12.74	2.31	1.60	1.75	2.27
HU10	3.46	2.36	4.53	2.88	2.39	3.69	0.79	0.83	0.81
HU21	2.51	2.87	1.87	2.55	2.55	1.22	1.30	2.93	2.93
HU22	6.07	5.27	2.99	1.69	2.62	4.94	2.59	3.35	3.24
HU23	4.93	5.04	3.28	4.54	6.02	4.97	2.88	4.46	3.20
HU31	4.37	2.51	3.86	2.50	2.50	4.83	4.12	4.16	4.19
HU32	4.74	6.19	8.80	6.04	5.27	6.38	7.36	6.04	5.96
HU33	2.20	2.16	2.25	2.22	2.22	2.31	2.37	2.35	2.37
PL11	5.81	7.50	6.09	3.97	3.64	5.30	5.52	5.44	5.29
PL12	4.81	4.08	3.60	4.96	5.24	2.39	3.18	3.14	3.08
PL21	4.48	4.31	1.82	2.10	5.59	1.94	3.05	2.78	3.17
PL22	9.83	2.96	18.93	2.80	3.61	9.73	1.96	6.36	6.55
PL31	4.44	3.33	1.94	2.12	3.97	2.23	1.59	1.62	1.63
PL32	4.79	6.60	8.22	8.65	7.73	6.96	7.11	7.99	5.84
PL33	3.10	3.88	7.18	3.25	4.30	5.10	5.03	3.61	4.99
PL34	3.80	5.17	4.38	10.54	4.49	6.18	5.58	5.76	3.26
PL41	7.12	6.30	6.19	7.14	6.56	4.53	5.17	5.34	5.39
PL42	4.98	4.95	2.47	2.47	2.53	2.32	2.92	2.22	2.20
PL43	3.35	2.41	3.08	6.68	3.97	1.98	2.74	3.74	2.82
PL51	36.14	26.97	28.49	26.53	27.08	17.23	20.82	28.83	20.76
PL52	3.06	1.78	2.88	2.75	2.70	0.86	2.39	2.33	1.65
PL61	7.52	8.51	7.58	9.56	9.56	4.58	5.41	5.88	5.91
PL62	11.73	5.97	3.16	4.19	4.84	2.78	3.70	3.53	3.17
PL63	17.98	11.07	33.43	22.49	21.03	9.73	9.66	19.62	19.62
RO11	7.64	3.46	3.80	4.25	4.41	3.30	3.06	3.14	3.25
RO12	4.88	5.04	10.84	4.89	4.66	11.53	1.07	1.13	1.26
RO21	7.96	8.13	7.28	8.17	8.14	5.24	6.25	6.25	6.26
RO22	2.15	2.15	4.26	2.19	2.63	7.48	4.24	5.19	6.00
RO31	2.67	3.70	4.24	3.29	14.12	7.21	5.67	3.36	3.35
RO32	30.72	33.12	19.29	23.24	25.71	11.15	11.83	10.64	10.23
RO41	8.41	7.36	5.92	7.90	10.17	4.89	4.53	3.74	3.70
RO42	10.42	10.69	8.02	11.06	11.06	6.19	6.51	6.47	6.53

C.5 Robustness checks: alternative algorithms

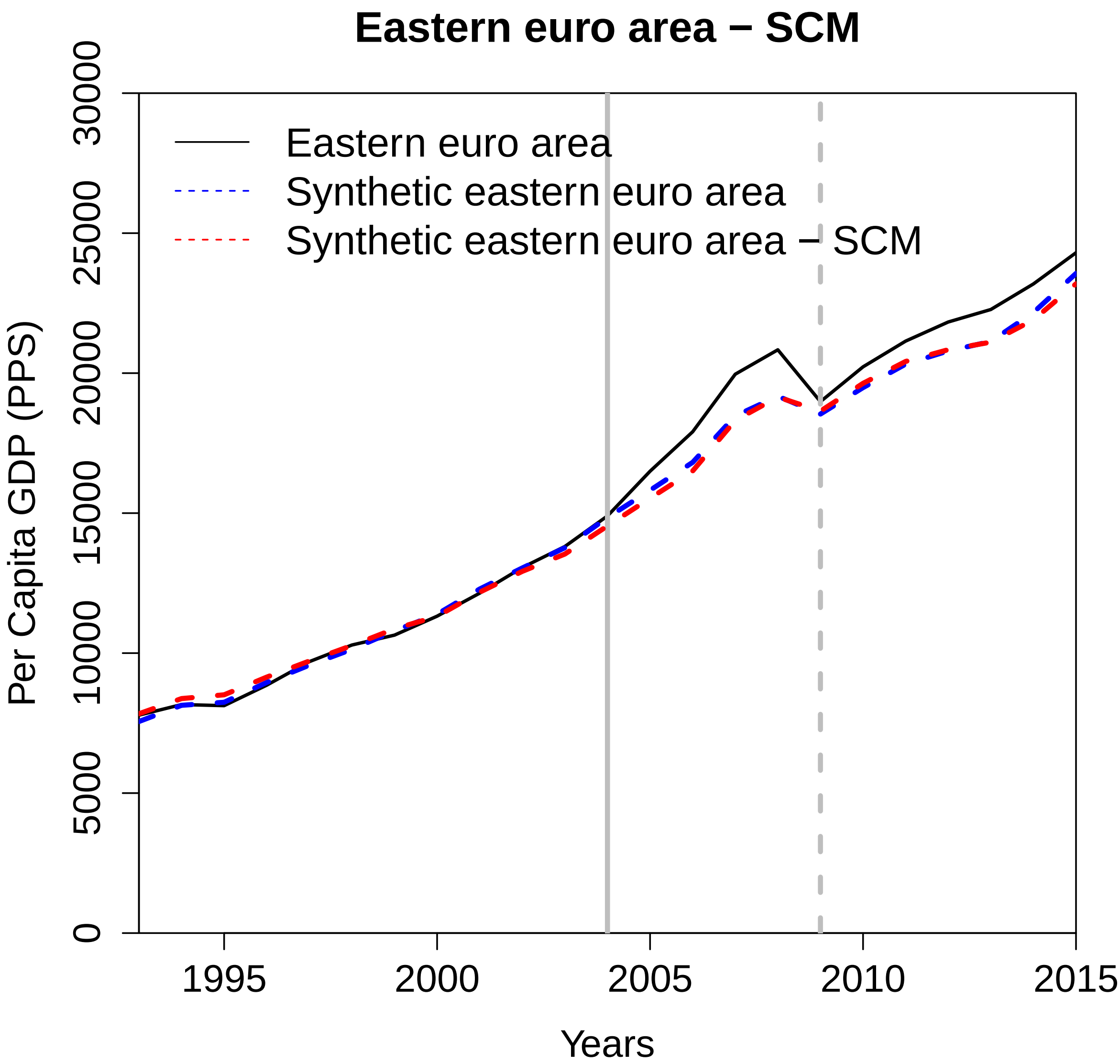
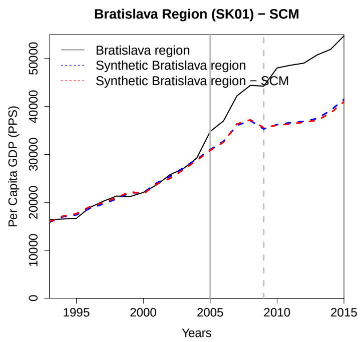
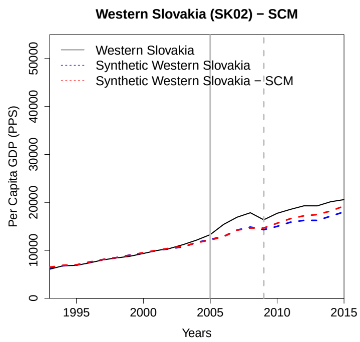


FIGURE C.4: Eastern euro area - SCM

Notes: The synthetic eastern euro area estimated with the SCM is obtained as an average of the nine synthetic regions estimated with the SCM.



(A)



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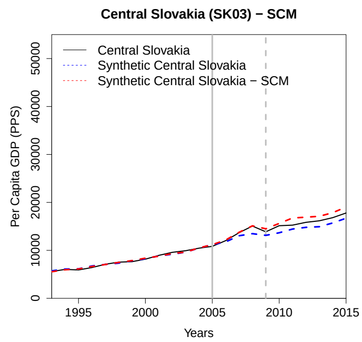

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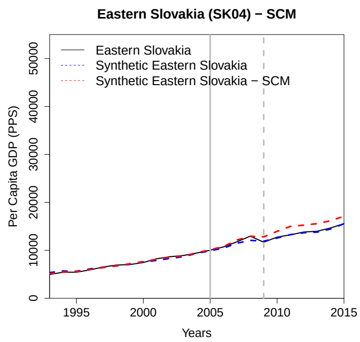

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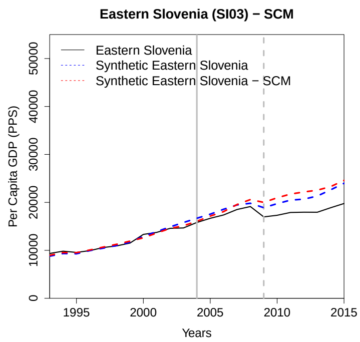

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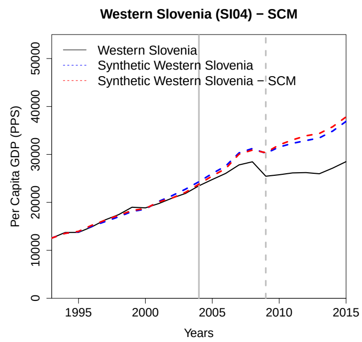

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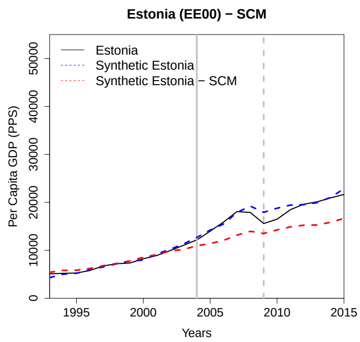

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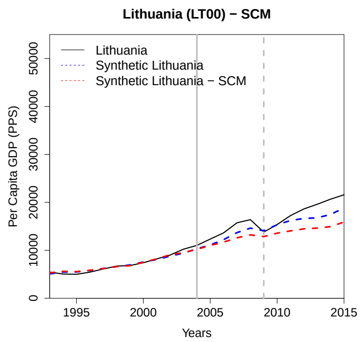

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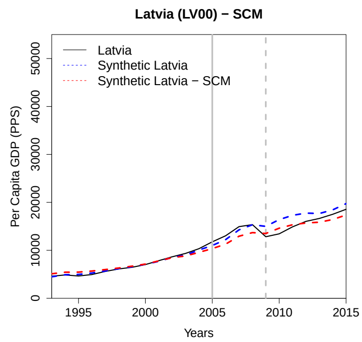


(I)

FIGURE C.5: Synthetic Control Method

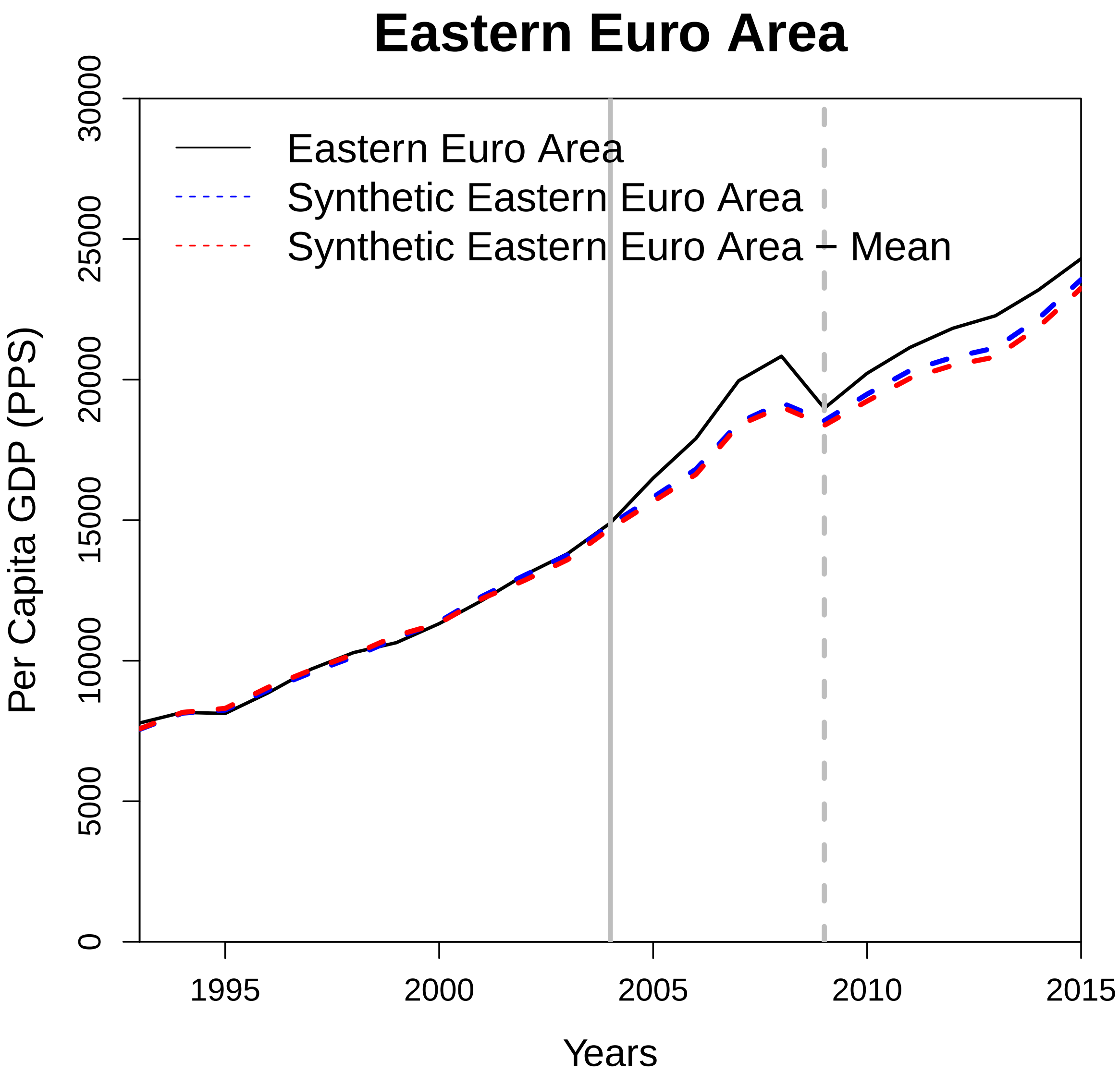


FIGURE C.6: Eastern euro area - Mean Balancing

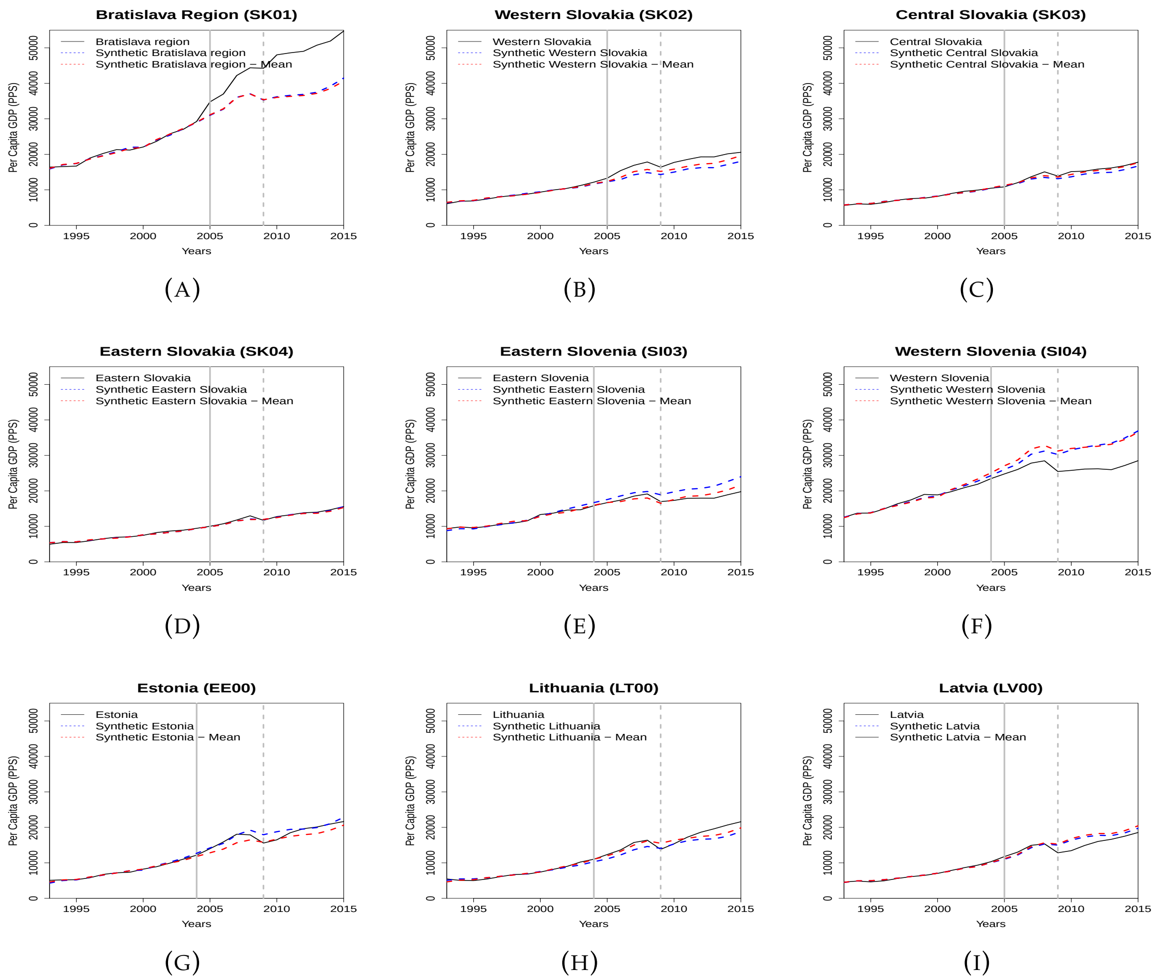
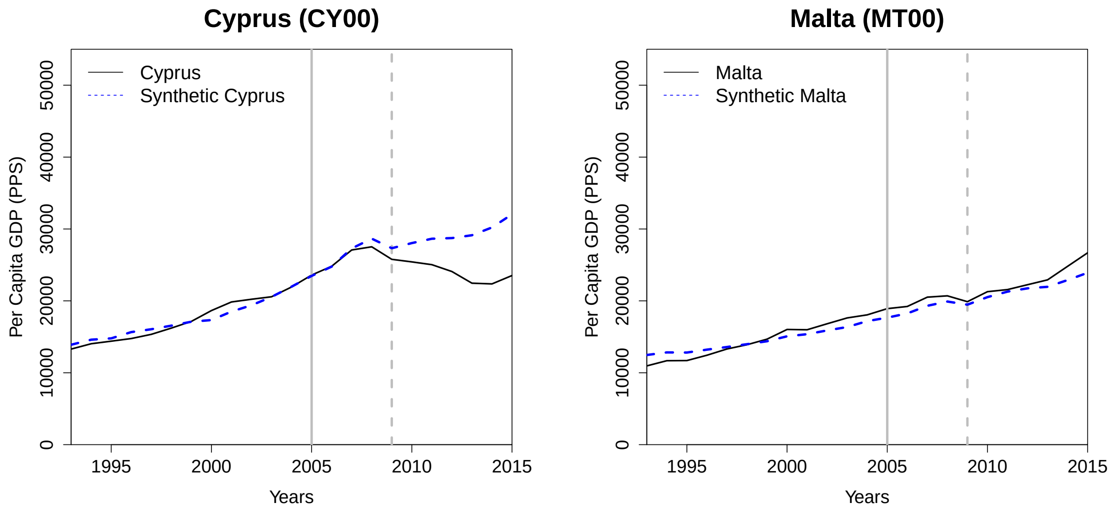


FIGURE C.7: Mean Balancing

C.6 Cyprus and Malta



(A) (B)

FIGURE C.8: Cyprus and Malta trends' in GDP per capita (NUTS-2 level)

Bibliography

Abadie, A., Diamond, A., & 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., & Hainmueller, J. (2011). Synth: An R Package for Synthetic Control Methods in Comparative Case. *Journal of Statistical Software*, *42*(13).

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

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

Abadie, A., & L'Hour, J. (2019). A penalized synthetic control estimator for disaggregated data. *working paper. Available at https://sites.google.com/site/jeremylhour/research.*

Abadie, A. (2021). Using synthetic controls: Feasibility, data requirements, and methodological aspects. *Journal of Economic Literature*, *59*(2), 391–425.

Ágh, A. (2017). Cohesive Europe or Core-Periphery Divide in the EU28: The regional challenge of dual crisis in the new member states. *Journal of Comparative Politics*, *10*(1), 4–24.

Alessi, L., Benczur, P., Campolongo, F., Cariboni, J., Manca, A. R., Menyhert, B., & Pagano, A. (2019). The Resilience of EU Member States to the Financial and Economic Crisis. *Social Indicators Research*, 1–30.

Amjad, M., Shah, D., & Shen, D. (2018). Robust synthetic control. *The Journal of Machine Learning Research*, *19*(1), 802–852.

Andrews, D. W. (2003). End-of-sample instability tests. *Econometrica*, *71*(6), 1661–1694.

Angelucci, M., & Di Maro, V. (2016). Programme evaluation and spillover effects. *Journal of Development Effectiveness*, *8*(1), 22–43.

Arkhangelsky, D., Athey, S., Hirshberg, D. A., Imbens, G. W., & Wager, S. (2019). *Synthetic difference in differences* (tech. rep.). National Bureau of Economic Research.

Artis, M., Banerjee, A., & Marcellino, M. (2006). *The central and eastern European countries and the European Union*. Cambridge University Press.

Athey, S., & Imbens, G. W. (2017). The state of applied econometrics: Causality and policy evaluation. *Journal of Economic Perspectives*, *31*(2), 3–32.

Athey, S., Bayati, M., Doudchenko, N., Imbens, G., & Khosravi, K. (2020). Matrix completion methods for causal panel data models. *arXiv:1710.10251v3*.

Backé, P., Dvorsky, S. et al. (2018). Enlargement of the euro area toward CESEE: Progress and perspectives. *Focus on European Economic Integration Q*, *3*, 43–56.

Barro, R. J., & Sala-i-Martin, X. (1992). Convergence. *Journal of Political Economy*, *100*(2), 223–251.

Barro, R. J., & Sala-i-Martin, X. (1995). *Economic growth*. MIT Press.

Bayoumi, T., & Eichengreen, B. (1993). *Shocking Aspects of European Monetary Unification*. Oxford: Cambridge University Press.

Becker, T., Daianu, D., Darvas, Z., Gligorov, V., Landesmann, M., Petrovic, P., Pisani-Ferry, J., Rosati, D., Sapir, A., & Di Mauro, B. W. (2010). Whither growth in central and eastern Europe? policy lessons for an integrated Europe. *Bruegel Blueprint Series*, *11*, 83.

Ben-Michael, E., Feller, A., & Rothstein, J. (2019). Synthetic Controls and Weighted Event Studies with Staggered Adoption. *arXiv:1912.03290v1*.

Ben-Michael, E., Feller, A., & Rothstein, J. (2020). The Augmented Synthetic Control Method. *arXiv:1811.04170v3*.

Botosaru, I., & Ferman, B. (2019). On the role of covariates in the synthetic control method. *The Econometrics Journal*, *22*(2), 117–130.

Cao, J., & Dowd, C. (2019). Estimation and inference for synthetic control methods with spillover effects. *arXiv preprint arXiv:1902.07343*.

Capello, R., Caragliu, A., & Fratesi, U. (2018). The regional costs of market size losses in a EU dismembering process. *Papers in Regional Science*, *97*(1), 73–90.

Cattaneo, M. D., Feng, Y., & Titiunik, R. (2019). Prediction intervals for synthetic control methods. *arXiv preprint arXiv:1912.07120*.

Cerqua, A., & Pellegrini, G. (2017). Industrial policy evaluation in the presence of spillovers. *Small Business Economics*, *49*(3), 671–686.

Charron, N., Dijkstra, L., & Lapuente, V. (2014). Regional governance matters: Quality of government within European Union member states. *Regional Studies*, *48*(1), 68–90.

Chernozhukov, V., Wüthrich, K., & Zhu, Y. (2020). An Exact and Robust Conformal Inference Method for Counterfactual and Synthetic Controls. *arXiv:1712.09089v6*.

Coudert, V., Couharde, C., Grekou, C., & Mignon, V. (2020). Heterogeneity within the euro area: New insights into an old story. *Economic Modelling*, *90*, 428–444.

Cox, D. R. (1958). Planning of experiments.

Dabrowski, M. (2019). The Economic and Monetary Union: Past, Present and Future. *CASE Research Paper No 497*, (497).

Doudchenko, N., & Imbens, G. W. (2017). Balancing, Regression, Difference-In-Differences and Synthetic Control Methods: A Synthesis. *arXiv:1610.07748*.

Drake, L., & Mills, T. (2010). Trends and cycles in Euro area real GDP. *Applied Economics*, *42*(11), 1397–1401.

Ferman, B., & Pinto, C. (2019). Synthetic controls with imperfect pre-treatment fit. *arXiv preprint arXiv:1911.08521*.

Fernández, C., & Garcia-Perea, P. (2015). The impact of the euro on euro area GDP per capita. *Working Paper*.

Fingleton, B., Garretsen, H., & Martin, R. (2015). Shocking aspects of monetary union: The vulnerability of regions in Euroland. *Journal of Economic Geography*, *15*(5), 907–934.

Firpo, S., & Possebom, V. (2018). Synthetic control method: Inference, sensitivity analysis and confidence sets. *Journal of Causal Inference*, *6*(2), 1–26.

Forastiere, L., Airoldi, E. M., & Mealli, F. (2020). Identification and estimation of treatment and interference effects in observational studies on networks. *Journal of the American Statistical Association*, 1–18.

Forlati, C. (2015). On the benefits of a monetary union: Does it pay to be bigger? *Journal of International Economics*, *97*(2), 448–463.

Frankel, J. A., & Rose, A. K. (1998). The endogenity of the optimum currency area criteria. *The Economic Journal*, *108*(449), 1009–1025.

Gabriel, R. D., & Pessoa, A. S. (2020). Adopting the Euro: A synthetic control approach. *Available at SSRN 3563044*.

Gehler, M., & Graf, M. (2018). Austria, German Unification, and European Integration: A Brief Historical Background. *working paper-Cold War International History Project*.

Giannone, D., Lenza, M., & Reichlin, L. (2010). Business Cycles in the Euro Area. *Europe and the euro* (pp. 141–167). University of Chicago Press. http://www.nber.org/chapters/c11669

Gobillon, L., & Magnac, T. (2016). Regional policy evaluation: Interactive fixed effects and synthetic controls. *Review of Economics and Statistics*, *98*(3), 535–551.

Grossi, G., Lattarulo, P., Mariani, M., Mattei, A., & Öner, Ö. (2020). Synthetic control group methods in the presence of interference: The direct and spillover effects of light rail on neighborhood retail activity. *arXiv preprint arXiv:2004.05027*.

Hallet, M. (2004). *Regional integration effects of the euro: What is the empirical evidence after the first years?* Hannover: Verlag der ARL-Akademie für Raumforschung und Landesplanung.

Hazlett, C., & Xu, Y. (2018). Trajectory balancing: A general reweighting approach to causal inference with time-series cross-sectional data. *Available at SSRN 3214231*.

Holland, P. W. (1986). Statistics and causal inference. *Journal of the American statistical Association*, *81*(396), 945–960.

Huber, M., & Steinmayr, A. (2019). A framework for separating individual-level treatment effects from spillover effects. *Journal of Business & Economic Statistics*, 1–15.

Imbens, G. W., & Rubin, D. B. (2015). *Causal inference in statistics, social, and biomedical sciences*. Cambridge University Press.

Jonard, F., Lambotte, M., Ramos, F., Terres, J., & Bamps, C. (2009). Delimitations of rural areas in Europe using criteria of population density, remoteness and land cover. *JRC Scientific Report, EUR, 23757*.

Kahanec, M., Zimmermann, K. F. et al. (2016). Post-enlargement Migration and the Great Recession in the E (M) U: Lessons and policy implications. *UNU-MERIT Working Papers*, *66*, 34.

Kellogg, M., Mogstad, M., Pouliot, G., & Torgovitsky, A. (2020). Combining Matching and Synthetic Controls to Trade off Biases from Extrapolation and Interpolation. *National Bureau of Economic Research*.

Kravtsova, V., & Radosevic, S. (2012). Are systems of innovation in Eastern Europe efficient? *Economic Systems*, *36*(1), 109–126. https://EconPapers.repec.org/RePEc:eee:ecosys:v:36:y:2012:i:1:p:109-126

Kuokštis, V. (2011). What type of capitalism do the Baltic countries belong to? *Emecon Employment and economy in Central and Eastern Europe*, *2*(1), 1–16.

Li, K. T. (2019). Statistical inference for average treatment effects estimated by synthetic control methods. *Journal of the American Statistical Association*, 1–16.

McKinnon, R. I. (1963). Optimum currency areas. *The American Economic Review*, *53*(4), 717–725.

Mellace, G., & Pasquini, A. (2019). Identify more, observe less: Mediation analysis synthetic control. *arXiv e-prints*, Article arXiv:1909.12073, arXiv:1909.12073.

Mundell, R. A. (1961). A theory of optimum currency areas. *The American Economic Review*, *51*(4), 657–665.

Neyman, J. (1923). On the application of probability theory to agricultural experiments. essay on principles. section 9. *Translated in Statistical Science*, 465–480.

Neyman, J., & Iwaszkiewicz, K. (1935). Statistical problems in agricultural experimentation. *Supplement to the Journal of the Royal Statistical Society*, *2*(2), 107–180.

Pike, A., Rodrıguez-Pose, A., & Tomaney, J. (2016). *Local and regional development*. Routledge.

Puga, D. (2002). European regional policies in light of recent location theories. *Journal of Economic Geography*, *2*(4), 373–406.

Puzzello, L., & Gomis-Porqueras, P. (2018). Winners and losers from the Euro. *European Economic Review*, *108*, 129–152.

Rodrıguez-Pose, A., & Garcilazo, E. (2015). Quality of government and the returns of investment: Examining the impact of cohesion expenditure in european regions. *Regional Studies*, *49*(8), 1274–1290.

Rose, A. K., & Van Wincoop, E. (2001). National money as a barrier to international trade: The real case for currency union. *American Economic Review*, *91*(2), 386–390.

Rozmahel, P., Kouba, L., G.á, L., & Najman, N. (2013). *Integration of Central and Eastern European Countries: Increasing EU Heterogeneity?* (Tech. rep.). WWWforEurope Working Paper.

Rubin, D. B. (1974). Estimating Causal Effects of Treatments in Randomized and Nonrandomized Studies. *Journal of Educational Psychology*, *66*(5), 688–701.

Rubin, D. B. (1980). Randomization analysis of experimental data: The fisher randomization test comment. *Journal of the American statistical association*, *75*(371), 591–593.

Schinasi, G. J., Lipschitz, L., & McDonald, D. (1990). Monetary and financial issues in German unification. *German Unification: Economic Issues. International Monetary Fund, Occasional Paper*, (75), 144–154.

Sobel, M. E. (2006). What do randomized studies of housing mobility demonstrate? causal inference in the face of interference. *Journal of the American Statistical Association*, *101*(476), 1398–1407.

Solow, R. M. (1956). A contribution to the theory of economic growth. *The Quarterly Journal of Economics*, *70*(1), 65–94.

Stiglitz, J. E. (2017). The fundamental flaws in the euro zone framework. *The euro and the crisis* (pp. 11–16). Springer.

Swan, T. W. (1956). Economic growth and capital accumulation. *Economic Record*, *32*(2), 334–361.

Thissen, M., Van Oort, F., Diodato, D., & Ruijs, A. (2013). *Regional competitiveness and smart specialization in Europe: Place-based development in international economic networks*. Edward Elgar Publishing.

Vazquez-Bare, G. (2017). Identification and estimation of spillover effects in randomized experiments. *arXiv preprint arXiv:1711.02745*.

Verstegen, L., van Groezen, B., & Meijdam, A. (2017). Benefits of EMU participation: Estimates using the synthetic control method. *CentER Discussion Paper Series*.

Xu, Y. (2017). Generalized Synthetic Control Method: Causal Inference with Interactive Fixed Effects Models. *Political Analysis*, *25*(1), 57–76. https://doi.org/10.1017/pan.2016.2

Žúdel, B., & Melioris, L. (2016). *Five years in a balloon: Estimating the effects of euro adoption in Slovakia using the synthetic control method* (tech. rep.). OECD Publishing.