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The effect of firms reporting to the Carbon disclosure project on their CO_2 emissions

An empirical study based on the synthetic control approach

Doctoral Thesis

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by

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"Mojí mamince!"

Typeset with LaTeX

Contents

List of Tables

List of Figures

List of Scripts

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Abstract

Whoever is not “green” is not “in”. That’s the latest trend of the market. This environmental movement pushes the companies to review their policies and assure a sustainable development by reducing their Carbon Dioxide (CO2) emissions and use of natural resources or in general show an eco-friendly behaviour.

The objective of our work is to assess the pertinence of green policy introduction at the business level. For our analysis, we are using unique data sets of the firm’s CO2 emissions. We built our data by adding several firms’ characteristics to an initial database provided by South Pole Group. Based on particular companies’ specificities we were then able to select the suitable treated and control groups.

Carbon Disclosure Project (CDP) is a non-profit organisation allowing companies to report and manage their emissions, climate risk and reduction goals. And in our study, we intend to evaluate whether signing up to the CDP has a positive effect on the firms’ emissions.

It is a typical causal effect evaluation problem that we solve using a relatively new approach called “Synthetic Control Method (SCM)” introduced by Abadie and Gardeazabal (2003). The objective of this method is to build the synthetic control unit, which is the weighted combinations of available control units that most closely resemble the treated unit before the treatment in term of different characteristics. This synthetic control unit allows us to define the counterfactual outcome, that is then compared to the actual outcome to evaluate the treatment effect. We chose the synthetic control method because it allows researchers to analyse phenomena that occur in a limited population or that apply to only a small number of firms, which is ideally suited to our problematic.

Almer and Winkler (2013) used this method in environmental problematic, but to our knowledge, it has never been applied to evaluate firms’ politics, and indeed we will use this approach to analyse the environmental programme at a company level.

To complete the investigation of the general impact of this program on firms’ emissions, we also focus on three geographic regions: the United States (US), the United Kingdom (UK), and the rest of European Union (EU). Moreover, the study also covers the comparison of results between all sectors of activities.

Introduction

Nowadays, most of the world is aware of the irreversible climate change and the impact of this instance on the entire planet. As covered in the Stern Review (Stern (2006)), even the most powerful economies, who are the biggest greenhouse gas emitters, are not prevented from the effect of the raising temperature. This phenomenon increases the need of “green” and sustainable economies to mitigate the climate change and assure the future. Consequently, the companies are pushed to quickly and significantly cut down their greenhouse gas emissions and revise their actions in this direction.

Many policies, international agreements and regulations, that are also introduced in this work exist to control the greenhouse gas emissions and mitigate the climate change. The question that naturally arises is “how do we evaluate the pro-environmental behaviour?”

To answer that, numerous studies assessing the introduction of climate agreements were conducted on the macro scale. For example, we can cite work of Aichele and Felbermayr (2012) or Almer and Winkler (2013), who evaluated the Kyoto Protocol. Almer and Winkler (2013) used the synthetic control method in environmental problematic, but to our knowledge, it has not been applied to assess a firm’s policy such as environmental programmes at the company level. This lack in the application of the synthetic control method catches our attention.

The primary objective of our study is to assess the pertinence of green policy introduction at the business level. More precisely, we intend to evaluate whether participating to the Carbon Disclosure Project[1], as one of the binding reporting standards, has a positive effect on the firm’s emissions. This is a typical causal effect problem that we solve by using a relatively new method, that is the synthetic control approach.

The synthetic control method is one of many program evaluations’ approaches that seeks the estimation of the treatment effect of particular program or treatment. Introduced by Abadie and Gardeazabal (2003), this approach provides a data-driven procedure to estimate synthetic control units based on a weighted combination of control units that approximates the characteristics of the unit exposed to the treatment. Moreover, with this approach, we can estimate the treatment effect in settings where a single unit is exposed to treatment, or where we dispose few historical data. We

[1] CDP is a not-for-profit organisation that runs the global disclosure system for investors, companies, cities, states and regions to manage their environmental impacts. Founded in 2003 and based in the United Kingdom. Its primary goal is to help the corporations and cities to disclose the greenhouse gas emissions and assist them to manage the environmental risk.

start from the principle that a combination of comparison units often provides a better comparison for the unit exposed to the intervention than any comparison unit alone. By its characteristics, the synthetic control method allows us to generate treatment effects for each of the studied companies, and perform statistical inferences.

Furthermore, our work covers several research questions. The first general question asks if there is a positive impact of the Carbon Disclosure Project on the participating companies' emissions. The second research question is focussed on the comparison of the results between three different geographic regions, which are the EU, the UK, and the US. Note that it was the similarity in the economic development and the environmental strategies that lead us to the choice of these regions. Last research question inquires whether there is one of the nine sectors of activities (Financials (FINA), Health Care (HC), Information Technology and Telecommunication (ITTE), Consumer Discretionary (CD), Consumer Staples (CS), Industrials (INDU), Energy (ENGY), Materials (MATR), Utilities (UTIL)), or any of three emitter groups (light, medium, or heavy carbon dioxide emitters), that would be more successful in the program participation than the others.

Another objective of our work is to do a complete and detailed review of the synthetic control approach. Note that this method is covered in four papers by Abadie and al. (Abadie and Gardeazabal (2003); Abadie et al. (2010, 2011, 2015)), where the authors assess different political problems and develop the synthetic control method, as well as the tests used to evaluate the significance of the results. In our work, we do review all the papers and present the main elements of the method, the way of showing the results, and all different statistical inferences that the approach allows. Moreover, we also cover the application of the synthetic control method in the statistical program R Core Team (2013) and present how we used the package "Synth" developed by Hainmueller and Diamond (2015).

An essential element to mention is the quality and uniqueness of our database. Collecting the historical data on the carbon dioxide emissions on the firm's level is still quite a challenging task, as the companies are not usually holding the historical data. With the contribution of the South Pole Group, we were able to collect the data for a total of 139 companies between the years 2005 to 2013. This data contains carbon dioxide emissions and other characteristics of the firms that do or do not participate in the Carbon Disclosure Project. Moreover, the data covers nine different sectors and three geographic regions.

We structured our work in two parts. The first one gives a theoretical overview of the program evaluation methods and the synthetic control method in particular. Moreover, we also introduce the environmental problematics at the international and firm's level, and we present the Carbon Disclosure Project into more details. The second part presents the empirical application of the synthetic control method on the environmental problematic, more specifically, the evaluation of the Carbon Disclosure Project. We introduce the research questions, data and model implementation, as well as the estimations and the results of the study.

Chapter 1 introduces the problematic of treatment effect estimation in political and economic sciences. We review the historical development of the program evaluation methods. These techniques assess the effect of the exposure of a set of units to a program or treatment on some outcome in two different backgrounds, the randomised experiment or the observational studies. In the randomised experiment, all is under the control of the investigator, and in the observational studies, the system under study is outside his control. To estimate a treatment effect there exists different techniques as the social experiment, the regression model, the matching estimators, or the instrumental variables. These methods, covered in various articles of scientists as Neyman, Rubin, LaLonde, Holland, and many others, are also briefly reviewed in the first chapter. Also, we introduce the main elements of program evaluation methods as the potential outcome, the treatment effect, as well as different estimators and assumptions.

Chapter 2 goes further in the problematic of the treatment effect estimation and presents a relatively new approach, the so-called synthetic control method, which estimates the impact of interventions. The synthetic control method is the primary approach used in our work to evaluate the treatment effect. The first section of this chapter presents the series of main articles on the synthetic control method. The second section introduces the methodology of the synthetic control method. In this part, we introduce the basic notations and definitions, the driving model and its application, the optimisation problem, the way of presenting the results of the analysis, and we finish with a short review of the advantages and limitations of the synthetic control method in comparison to the standard regression method. The final section describes the statistical inferences' tools as the placebo tests, and the root mean squared prediction error or the robustness analysis.

Chapter 3 introduces the problematic of the climate change, the necessity of the reduction of carbon emissions and how this is regulated on the international and firm's level. In the first section, we present the leading organisations and regulations related to the climate change, as the contributions of the United Nation, or the Kyoto Protocol. The second section overview the main disclosing programs on the firm's level. Moreover, we present some initiatives and regulations promoting the low carbon economy in the European Union, the United Kingdom, and the United States (as these regions are studied in our work). The last section of this chapter presents the Carbon Disclosure Program, one of the binding reporting standards that are evaluated in our study.

Chapter 4 primary objective is to introduce the research questions, data and model implementations. We start with a brief literature review of firm's environmental studies, and open to the section that develops our frame of hypothesis and three research questions for the study. As the next step, we present the creation of the database, the variables and provide the descriptive statistics. The third section is dedicated to the methodological part of our study, where we present the model, the application of the synthetic control method, and the statistical inference tests. The final section introduces the implementation of the model with the statistical program R. We introduce the library "Synth", the R package developed by Hainmueller and Diamond (2015) for synthetic control methods in comparative case studies. Moreover, we present the library "Mylib", a package we built, that contains different functions created to adapt the package "Synth" on our case. We also present the "Jobs" that produce the synthetic control analysis and show the outcomes of the most important functions.

Chapter 5 is focussed on estimations, presentation of the results and gives the answers to the three research questions. The first section presents the results of the analysis regardless of the sector or the geographic region of the firms. The second section compares the results between the regions. The third section analysis the results in different areas of activities. And the last section presents a short conclusion of the study.

Part I

Theoretical part

Chapter 1

Historical review and introduction to the program evaluation methods

In economics or other social sciences, in particular, many empirical questions are about evaluating the effect of exposure to a set of units to a program or treatment on some outcome. We mean by term "units" the "economic agents" such as individuals, households, schools, firms, countries. The term "treatment", also known as exposure to program, experiment, or intervention, refers for example to job search assistance programs, laws or regulations, environmental or technology exposures.

To assess the causal effect of particular program or policies we make use of the program evaluation methods. The term "causal effect" refers to the comparisons of so-called potential outcomes, pairs of outcomes defined for the same unit given different levels of exposure to the treatment. In this work, we are limited to settings with binary treatments, and we are interested in the evaluation of the "treatment effect", comparison of the two outcomes for one unit that would result from exposure to alternative causal state when exposed and not exposed to the treatment. As we cannot observe the same unit exposed and not exposed to the treatment, only one of the potential outcomes is realisable. And to evaluate the treatment effect we make use of the counterfactual outcome, which is the not realised potential outcome that has to be estimated.

While estimating the treatment effect the researcher faces two kinds of backgrounds: randomised experiment or observational studies. In the randomised experiment, the system under study is under the control of the investigator. This means that the researcher selects the assignment to the treatment, nature and the measurement procedures used. By contrast in an observational study these features, in particular, the allocation to the treatment, are outside the investigator's control.

The treatment effects can be estimated by using, for example, social experiments, regression models, matching estimators, or instrumental variables. A standard to estimate the treatment effect is the potential outcome model of causal inference published by Rubin (1974) in his revolutionary article on the counterfactual model for causal analysis of observational data. Rubin's model becomes the basis of the program evaluation method, and in all our work we also think of the causal relationship in term of the potential outcome framework.

In this chapter, first, we make a short historical review of program evaluation methods. In the second section, we present the basic notions, definitions, estimators and assumptions used in the evaluation methods. Note that as we cannot cover all the methods, for more detailed review, see Imbens and Wooldridge (2008) which is an excellent document offering an in-depth overview of the research made in the previous two decades on the econometric and statistical analyses of the effects of programs or treatments. Another good review, focusing more on technical detail of the analysis is Angrist and Pischke (2008). Moreover, in annex A.1 we present a section covering the basic ideas behind matching and Difference-in-differences (DID) methods.

1.1 Historical review of program evaluation methods

In the introduction, we mentioned that the central problem in program evaluation methods is the assessment of the causal effect. This problematic does have a long history both in statistics and econometrics. In this chapter we review the main research done in program evaluation, starting with the introduction of potential outcome framework and following by three subchapters developing the randomised and observational studies methods.

Historically, potential outcomes were first approached in 1923 by Neyman (Splawa-Neyman et al. (1990)). Rubin notes on Neyman's work: *"The most important contribution of Neyman is its explicit use of notation U_{ik} to indicate the yield of plot k if exposed to variety i drawn accordingly to the urn schema. The U_{ik} is a potential yield, not an observed yield because i indexes all varieties and k indexes all plots, and each plot is exposed to only one variety. This notation become the standard for describing possible outcomes of randomised experiment, and allows for causal effect and causal estimates to be defined without any probability model for the data"* (Rubin (1990a, pp. 473-474)).

In the first half of century, the potential outcome framework was sowing its seeds. Neyman's work was followed by Fisher (1935), Cochran and Cox (1950), Kempthorne (1952), Cox (1958) and other articles focusing on random experiments. The potential outcomes were also used in economics, by Haavelmo (1943) in the simultaneous equations models, and in the econometric analyses of production functions, or in labour market settings in Roy's model (Roy (1951)).

But it is only in the second half of the past century that the potential outcome model was officially founded. In 1974 Rubin pioneered the statistical framework for the problem of potential outcome and extended it to the analysis of observational studies, where the units are not randomly assigned to the treatments (see Rubin (1974)). Rubin continued to develop and formalise the model in series of papers[1]. Holland (1986) overviewed his work and labelled the Rubin's formulation as Rubin's Causal Model. By means of this model, we can formalise basic intuitions concerning cause and effect and above all, analyse the causal effect.

[1] Rubin (1977, 1978, 1980, 1981, 1990b).

Apart of Rubin, an important contribution to the development of the evaluation methods was in the 90's and is due to the researchers as Ashenfelter (1978), Heckman and Robb (1985a), LaLonde (1986), or Manski (1990), and their focus on the evaluations of labour market programs in observational settings.

Resulting from Rubin's model, the program evaluation methods can be divided into two groups on the relationship between treatment assignment and the potential outcome. The first class of methods covers all the approaches with the randomised assignment to treatment. The second class of evaluation methods includes all methods, more common in economics, with the data from observational studies. In the observational setting itself, we distinguish two other subclasses. The first one holds the assumption of unconfoundedness[2], and the other one relaxes the unconfoundedness assumption. We present different classes of methods to estimate the treatment in the following sections.

1.1.1 Treatment effect in randomised experiments

The core characteristic of non-observational studies on the program evaluation is the independence between the treatment assignment and the covariates as well as the potential outcome. The randomised selection of individuals to a program presents ethics problem, so these methods are rather rare in economics. Note that it has been used in the case of some labor market evaluations (e.g., LaLonde (1986), Ashenfelter (1978)), and recently, there has been a significant number of experiments in development economics (e.g., Duflo (2001), Banerjee et al. (2007)), or behavioural economics (e.g., Bertrand and Mullainathan (2004)).

In general, using experimental data makes the statistical analysis straightforward, as we can obtain an unbiased estimator for the average effect of the treatment and improve the precision of the estimation by adding some covariates in the regression function. On the one hand, in economics, randomisation has never been regarded as the exclusive method for establishing causality. But on the other hand, LaLonde (1986) suggested that widely used econometric methods were unable to replicate the results from experimental evaluation. It was this point that encouraged governments to include the experimental evaluation of job training programs, but it has not had a long-lasting success. As previously mentioned, there has been the recent progression in the experimental studies for development economics. The majority concerned educational issues, and from the inception, economists have been heavily involved in the construction of optimal design.

[2]Unconfoundedness assumes that beyond the observed covariates there are not (unobserved) characteristics of the individual associated both with potential outcomes and treatment.

1.1.2 Treatment effect under unconfoundedness

The first class of program evaluation methods in observational studies concerns the methods that keep the assumptions of unconfoundedness, or overlap[3] or the combinations the two assumptions referred by Rosenbaum and Rubin (1983) as the strong ignorability assumption. Many different semi-parametric estimators exist, and they are classed in three groups of estimation methods presented in this section: regression methods, methods relying on propensity score and matching methods.

The regression methods for estimating average treatment effects went far beyond the simple parametric models, and two general directions have been explored. The first direction concerns the local smoothing, where Heckman et al. (1997) and Heckman et al. (1998) consider this method for estimating kernel and local linear regression functions. The second direction is the flexible global approximation, such as series or sieve estimators studied in Hahn (1998) or Chen et al. (2008).

The second group of methods to estimate different classes of estimators is based on the propensity score. These methods are founded on the results from Rosenbaum and Rubin (1983), and different methods are proposed. The first one uses the propensity score in place of the covariates in regression analysis (see Heckman et al. (1998)). The second one, stratification, adjusts for differences in the propensity score. The idea comes from Rosenbaum and Rubin (1983), and it is to partition the sample into strata by values of the propensity score, and then analyse the data within each stratum as if the propensity score was constant. In this case, the observations in the strata could be interpreted as coming from a completely randomised experiment. The third method is based on weighting, as the weighted estimator or the inverse probability weighting estimator (see Hirano et al. (2003)).

The last method to estimate different classes of estimators is matching. Matching estimators, widely used in practice because of their simplicity, use the closest neighbours from the opposite group. Given the matched pairs, the treatment effect within a pair is estimated as the difference in outcomes, and the overall average as the average of the within-pair differences. The matching estimator has been widely studied by Rosenbaum, Rubin, Heckman or Abadie[4]. Because matching is a component of the SCM used for our analysis, we present basics of the matching method in the annexe .

Imbens and Wooldridge (2008, pp. 20) states that: *"Although still widely used in practice, we do not recommend the basic methods, relying on the regression, propensity score methods, and matching, in practice."* They proposed the use of several mixed methods. The first combines regression and propensity score weighting but is not widely used in economic applications. The second combines the sub-classification and regression and is one of the most attractive estimation methods in practice. The last method merges matching with regression and is also supposed to be a very good technique to estimate the treatment effect.

[3]Overlap assumption implies that the support of the conditional distribution of the covariates given the non-participation to the treatment overlaps completely with that of the conditional distribution of the same covariate given the participation to the program.

[4]Rosenbaum (1989, 1995, 2002); Rubin (1973b, 1979); Heckman et al. (1998); Abadie and Imbens (2006).

1.1.3 Treatment effect without unconfoundedness

The third class of methods based on the assignment mechanism contains all other assignment mechanisms in observational studies with some dependencies on potential outcomes. These methods relax or completely drop the hypothesis of unconfoundedness and either replace it with another assumption or do not. There exist the multitude of methods, but the most prominent ones are: bounds analyses, sensitivity analyses, instrumental variables, regression discontinuity and difference-in-differences.

Bounds analyses were developed in series of papers and books by Manski[5]. This method simply drops the unconfoundedness assumption. Moreover, it supposes that the parameters of interest are not identified and can be bounded between two values and researcher may add some assumptions regarding the estimands.

Approaches based on the sensitivity analyses partially relax the unconfoundedness assumption. They include two main methods which are Rosenbaum's method to sensitivity analysis (Rosenbaum and Rubin (1983)) and the Rosenbaum-Rubin approach to sensitivity analysis (Rosenbaum (1995)). By sensitivity analyses, we examine the robustness of the results by the modest violation of the unconfoundedness assumption, which introduces a presence of unobserved covariates that are correlated, both with the potential outcomes and with the treatment indicator.

Instrumental variables method relies on the presence of additional treatments, so-called instruments, which satisfy specific exogeneity and exclusion restriction[6]. The formulation of these methods in the context of potential outcome framework is presented in Imbens and Angrist (1994), Angrist et al. (1996), where they focus on binary or multi-valued instruments and local average treatment effects.

Regression discontinuity methods have a long tradition in psychology and applied statistics, but it is only recently that these methods attracted more attention in economic research. These methods have two general settings: the sharp and the fuzzy regression discontinuity design[7]. Hahn et al. (2001, pp. 201) specifies: *"The regression discontinuity data design is a quasi-experimental design with the defining characteristic that the probability of receiving treatment changes discontinuously as a function of one or more underlying variables."*

Difference-in-differences is one of the most popular tools for applied research in economics to evaluate the treatment of some programs or politics. DID relies on the presence of additional data in the form of samples of treated or control units before and after treatment. Some applications were done by Ashenfelter and Card (1985) and recent theoretical work includes Abadie (2005) and others[8]. As the matching, the difference-in-differences is a base method to extend the synthetic control approach, and so we present them with more details in the annex A.1.1.

[5] Manski (1990, 2003, 2007).

[6] Exclusion restriction means that the instrument, Z, should not affect outcome variable, Y, when the covariate, C, is held constant.

[7] VanderKlaauw (2002), Hahn et al. (2001), Lee (2001), Porter (2003).

[8] Bertrand et al. (2004), Donald and Lang (2007), Athey and Imbens (2006).

1.2 Introduction to the program evaluation methods

The main point of the research in program evaluation is how to evaluate the causal effect of the units' exposure to one or more levels of treatment. As already mentioned, we are limited to settings with binary treatments, and we are interested in a comparison of two outcomes for the same unit depending on exposure to an experiment. The main problem is that we cannot observe more than one of the outcomes because the unit can be exposed to only one level of the treatment at a time. This problem is known as the "fundamental problem of causal inferences" covered in Holland (1986). Therefore to evaluate the treatment effect we need to compare distinct units being exposed to different experiments, these units are so-called "counterfactuals". Because of it, we encounter so-called selection bias. Selection bias is due to the individuals who choose to enrol in a program are by definition different from those who choose not to enrol.

The link between the selection bias, causality and treatment effect can be seen most clearly by using the potential outcomes framework. As we alluded before, one of the most common approaches to program evaluation is based on Rubin's work, in particularly it is the model for causal inference that Holland (1986) refers to as "Rubin's Causal Model".

In this section, we introduce the foundation of Rubin's model and describe different notions, notations and definitions used in the program evaluation methods. We start with the definition of the potential and realised outcomes, and we list main advantages of the potential outcome setup. We follow by main estimands for average treatment effect, and we finish this section with the most important assumption in causal effect modelling.

1.2.1 Potential outcome versus observed outcome

Before we define what the potential outcome is, we have to give some other notations and definitions. Let $i = 1, \dots, n$ be an individual, who decides whether to participate in the program. The unit that would receive the treatment is called treated unit, and the unit that does not receive the treatment is called control unit. We denote by g the participation to the program, respectively $g = I$ (I as intervention) is the exposure to the treatment, and $g = N$ (N as non-intervention) is the non-exposure to the treatment. The symbols n_I and n_N are the numbers of individuals that are in the program and those that are not, respectively.

Before the individuals decide to enrol in the program, there is the existence of two potential outcomes, Y_i^I and Y_i^N for each individual. Where Y_i^I indicates the outcome of individual i who decided to participate in the program, whereas Y_i^N indicates the outcome of non-participation. Both outcomes are potentially realisable, but only one of them is observable. The important concept to mention here is the counterfactual outcome. If the individual i attends the program then Y_i^I will be realised and Y_i^N will ex-post be a counterfactual outcome. On the other hand, if the individual i does not attend the program, then Y_i^N will be realised, and Y_i^I will ex-post be a counterfactual outcome. The causal effect in this context is based on comparisons of outcomes that would result from exposure to alternative causal state. The unit level causal effect of the treatment is defined as:

$$\alpha_i = Y_i^I - Y_i^N. \tag{1.1}$$

The decision to participate to the program is described by causal exposure variable, D_i, which is a dummy variable. D_i takes two values, respectively $D_i = 0$ for members of the population who are exposed to the control state or $D_i = 1$ for members of the population who are exposed to the treatment state. With respect to the exposure variable the realised outcome is defined as:

$$Y_i = Y_i^N + \alpha_i \cdot D_i = \begin{cases} Y_i^N & \text{if} \quad D_i = 0, \\ Y_i^I & \text{if} \quad D_i = 1. \end{cases}$$

Advantages of the potential outcome setup

There are several main advantages of the potential outcome setup over a framework based directly on realised outcome. First, it allows defining the causal effect before specifying the assignment mechanism, and without considering probabilistic properties of the outcomes or assignment. Second, it allows for heterogeneity in the effects of the treatment. Third, it allows formulating probabilistic assumptions in terms of potentially observable variables, rather than in terms of unobserved components. And finally, it clarifies where the uncertainty in the estimators comes from.

1.2.2 Estimands

Typically it is impossible to calculate individual causal effect, defined in equation (1.1), and we usually estimate the aggregate causal effect. There are several estimands commonly used. The first one is the population average treatment effect. And the population expectation of the unit-level causal effect is:

$$\begin{aligned} E[\alpha_i] &= E[Y_i^I - Y_i^N] \\ &= E[Y_i^I] - E[Y_i^N], \end{aligned}$$

where Y_i^I and Y_i^N are individual level potential outcomes, that is the potential outcome random variable for treated and control group.

Another estimand of the causal effect is the conditional average treatment effect. We define different conditional average treatment effects depending whether we are conditioning on the causal exposure variable, D, or on the covariates[9], C, or both of them. Here is the list of different estimands:

[9]Covariates define the characteristics of the units.

1. The conditional average treatment effect on the treated or the controlled is defined as:

$$\begin{aligned} E[\tau \mid D=1] &= E[Y_i^I - Y_i^N \mid D_i = 1] \\ &= E[Y_i^I \mid D_i = 1] - E[Y_i^N \mid D_i = 1], \\ E[\tau \mid D=0] &= E[Y_i^I - Y_i^N \mid D_i = 0] \\ &= E[Y_i^I \mid D_i = 0] - E[Y_i^N \mid D_i = 0]. \end{aligned}$$

2. The average causal effect conditional on the covariates in the sample is defined as:

$$E[\tau \mid C] = \frac{1}{n} \sum_{i=1}^{n} E\left[Y_i^I - Y_i^N \mid C_i\right].$$

3. The average over the subsample of treated or control units are:

$$\begin{aligned} E[\tau \mid D=1, C] &= \frac{1}{n_I} \sum_{i;D_i=1} E\left[Y_i^I - Y_i^N \mid C_i\right], \\ E[\tau \mid D=0, C] &= \frac{1}{n_N} \sum_{i;D_i=0} E\left[Y_i^I - Y_i^N \mid C_i\right]. \end{aligned}$$

As above, this is simply the average across the treated or control units in the subsample.

The four kinds of estimands presented in this sections are similar if the treatment effect τ is constant. The disparity between them depends on the degree of heterogeneity in the effect of the treatment. The big difference is not at the estimation stage, but there is an important divergence between the population and conditional estimates at the inference stage. If there is heterogeneity in the treatment effect, that sample average treatment effect is usually more precise than the population one.

Additionally to the previous estimands, there is another more general class of estimands, which includes the average causal effects for sub-populations and weighted average. This estimand is presented as:

$$E[\tau \mid \mathbb{A}] = \frac{1}{n_{\mathbb{A}}} \sum_{i:C_i \in \mathbb{A}} E\left[Y_i^I - Y_i^N \mid C_i\right],$$

where $n_{\mathbb{A}}$ is the number of units which belong to a class with certain characteristics that is $C_i \in \mathbb{A}$. This kind of estimator may be easier to estimate than the previous ones, and although it does not have as much external validity as estimates for the overall population, they may be much more informative for the sample at hand.

An other alternative class of estimands is the quantile treatment, which is fairly recent in economic literature, and is defined as:

$$\tau_q = F_{Y^I}^{-1}(q) - F_{Y^N}^{-1}(q).$$

This estimand τ_q is the difference between quantiles of the two marginal potential outcome distributions. Note that it differs from the following quantile of the unit level effect defined as:

$$\tilde{\tau}_q = F^{-1}_{Y^I - Y^N}(q).$$

To finish this short presentation of the estimators, we conclude by the following statement from Imbens and Wooldridge (2008, pp. 20): *"Most estimators currently in use can be written as the difference of a weighted average of the treated and control outcomes, with the weight in both groups adding to one:*

$$\hat{\tau} = \sum_{i=1}^{N} \omega_i \cdot Y_i, \qquad \textit{with} \qquad \sum_{i:D_i=1} \omega_i = 1, \qquad \sum_{i:D_i=0} \omega_i = -1,$$

where the ω_i is the weight depending on the full vector of assignments and matrix of covariates."

1.2.3 Assumptions

In this section, we present the main assumptions used in the causal effect modelling, which are: Stable Unit Treatment Value Assumption (SUTVA), ignorable treatment assignment, unconfoundedness, overlap and strong ignorability assumption. Furthermore, we also introduce the concept of confounding variable.

Stable unit treatment value assumption

The first assumption, resulting from Rubin's model, concerns the problematic of interactions between the individuals. This assumption, widely used in the literature, is the stable unit treatment value assumption, and has the following definition:

Assumption 1 (Stable unit treatment value assumption)**.**

By SUTVA assumption we suppose that treatments received by one unit do not affect outcomes for another unit. Only the level of the treatment applied to the specific individual is assumed to potentially affect outcomes for that particular individual.

This assumption seems plausible in most of the cases. But in some situations where the interaction exists[10] and may be a serious problem, we could use the no-interaction assumption, or we firmly model the interaction between the individuals.

[10] For example direct interaction between individuals or interaction via the market.

Ignorable treatment assignment

The second assumption concerns the treatment assignment, which is different in the experimental or observational context.

In randomised studies the assignment process is completely random and so the probability of being assigned to the treatment is independent of the potential outcome, that is:

$$P[D_i = d_i \mid Y_i^N, Y_i^I] = P[D_i = d_i].$$

As defined in Rubin (1978), ignorability of treatment assignment holds when the potential outcomes are independent of the causal exposure variable. For this case all variation in D is random, that is:

$$(Y_i^N, Y_i^I) \perp D_i,$$

where $\perp$ is the independence symbol. In this case the expected potential outcomes for treated and for control group are defined as follow:

$$\begin{aligned} E[Y_i^I \mid D_i = 1] &= E[Y_i^I \mid D_i = 0] = E[Y_i^I], \\ E[Y_i^N \mid D_i = 1] &= E[Y_i^N \mid D_i = 0] = E[Y_i^N]. \end{aligned}$$

On the other side, in observational studies, to keep the treatment assignment ignorable we resort to the confounding variable defined as:

Definition 1.1 (Confounding variable)**.**

We call “Confounding variable” all variables which denote individual characteristics and all variables that systematically determine all treatment assignment patterns and the potential outcomes. And we designed by $\mathbf{C}$ a vector of so-called confounding variables.

These variables help us to build the groups of similar characteristics (e.g. region, industry, revenue). Complete observation of $\mathbf{C}$ allows asserting that treatment assignment is “ignorable”, as we now explain, and then consistently estimate the average treatment effect.

Assumption 2 (Ignorable treatment assignment (Unconfoundedness))**.**

The treatment assignment mechanism is ignorable when the potential outcomes, and any functions of them, are independent of the treatment variables. Ignorable treatment assignment, also known as unconfoundedness, selection on observables or conditional independence assumption, is approved in randomised studies, and in observational studies depends on other variables. Unconfoundedness assumes that beyond the observed covariates there are not (unobserved) characteristics of the individual associated both with potential outcomes and treatment.

The definition of unconfoundedness is summarise by the following formula:

$$(Y_i^N, Y_i^I) \perp D_i \mid C_i. \tag{1.2}$$

In other words, it means that two individuals are identical if conditionally on $\mathbf{C}$, the probability to be assigned to the treatment program is independent of the potential outcome. In this case the expected potential outcomes for treated and for control group are defined as follow:

$$\begin{aligned} E[Y_i^I \mid C_i, D_i = 1] &= E[Y_i^I \mid C_i, D_i = 0] = E[Y_i^I \mid C_i], \\ E[Y_i^N \mid C_i, D_i = 1] &= E[Y_i^N \mid C_i, D_i = 0] = E[Y_i^N \mid C_i]. \end{aligned}$$

Strong ignorability

The unconfoundedness presented above, and the overlap, defined in the following definition, are the key assumptions underlying an analysis based on unconfoundedness introduced by Rosenbaum and Rubin (1983).

Assumption 3 (Overlap)**.**

$$0 < P(D_i = 1 \mid C_i = c) < 1.$$

Overlap assumption implies that the support[11] of the conditional distribution of C_i given $D_i = 1$ overlaps completely with that of the conditional distribution of C_i given $D_i = 0$ (see Imbens and Wooldridge (2008, pp. 21)). In other words, each unit in the defined population has some chance of being treated and some chance of not being treated.

In other words, it means that in the random experience each unit is assigned to the treatment with a certain probability.

In a overlap assumption the probability:

$$e(c) = P(D_i = 1 \mid C_i = c),$$

represents propensity score that is estimated with a random sample, $(D_i, C_i)_{i=1}^{N}$, and this provides some guidance for determining whether the overlap assumption holds.

The combination of the two assumptions, unconfoundedness and overlap, gives us what is known as strong ignorability (Rosenbaum and Rubin (1983)). And under the strong ignorability assumption, we estimate the average treatment effect by:

$$\begin{aligned}
\tau(x) &= \mathrm{E}\left[Y_i^I \mid C_i = c\right] - E\left[Y_i^N \mid C_i = c\right] \\
&= E\left[Y_i^I \mid D_i = 1, C_i = c\right] - E\left[Y_i^N \mid D_i = 0, C_i = c\right] \\
&= E\left[Y_i \mid D_i = 1, C_i = c\right] - E\left[Y_i \mid D_i = 0, C_i = c\right].
\end{aligned}$$

[11] Support of the function is the set of points where the function is not zero value.

Chapter 2

Synthetic control method

In the first chapter, we have introduced the problematic of treatment effect estimation in political and economic sciences. In this chapter, we go further on this subject and present a relatively new approach the so-called synthetic control method (SCM) that estimates the impact of interventions. This method is an extension of the difference-in-differences approach (see annex A.1.1). The synthetic control method was introduced in Abadie and Gardeazabal (2003) and knows an exponential use since 2010 after the introduction of the second article on SCM (Abadie et al. (2010)).

The main idea behind this method is that a combination of units often provides a better comparison for the unit exposed to the treatment than any single unit alone. SCM provides a systematic way to estimate the counterfactual unit so-called synthetic control, that is, a convex combination (weighted average) of available control units that most closely resemble the treated unit before the treatment in terms of the potential outcome and other relative predictors. The synthetic control allows us to identify the counterfactual outcome, which is then compared to the actual outcome to evaluate the treatment effect. Moreover, the SCM makes explicit the relative contribution of each available control unit and the degree of the similarity prior to the treatment between treated and control. Thanks to these characteristics, we can run different inferential exercises.

In this chapter, we expose the synthetic control method, which is the main approach used in our work in order to evaluate the treatment effect. The first section introduces the series of main articles on the synthetic control method. The second section presents the methodology of the synthetic control method. In this part, we introduce the basic notations and definitions, the driving model and its application, the optimisation problem, and we finish with a short review of the advantages and limitations of the SCM in comparison to the standard regression method. The final section describes the statistical inferences' tools as the placebo tests, and the root mean squared prediction error or the robustness analysis.

2.1 Synthetic control method in literature

The synthetic control method is a relatively new approach to evaluating the treatment effect in comparative case studies and was introduced by Abadie and Gardeazabal (2003). In this first article, the SCM is used to assess the economic effect of conflicts. A few years later, Abadie et al. (2010) applied the SCM to study the effect of an anti-tobacco legislation and in Abadie et al. (2015) to examine the economic consequence in case of political integration. Almer and Winkler (2013) introduced the SCM to deal with the environmental problematic, where they evaluate the effect of the commitment to the specific greenhouse gas targets under the Kyoto protocol on the CO2 emissions. In this section, we briefly present the evolution of the synthetic control method in the literature. In particular, we focus on the three main articles written by Abadie et al. that introduce the synthetic control method and develop the inference tools to evaluate the significance of the results.

Abadie and Gardeazabal (2003)

The article “The economic costs of conflicts: A case study of Basque country” by Abadie and Gardeazabal (2003) introduces the synthetic control method and the one-unit placebo test. The article studies the economic impact of conflict, using the terrorist conflict in the Basque Country as a study case.

To construct a “synthetic” control country without terrorism, the authors use the other Spanish regions for which the relevant economic characteristics resemble to the ones of the Basque country before the outset of Basque political terrorism in the late 60’s. The subsequent economic evolution, measured by per capita Gross Domestic product (GDP), of this “counterfactual” Basque country without terrorism is compared to the actual evolution of per capita GDP of the Basque country. The post-treatment gap between the two outcome variables represents the effect of terrorist activities. The gap shows negative effects of the terrorist activity on the economic evolution of the Basque country.

In order to test the relationship between the gap and the terrorist activity Abadie and Gardeazabal (2003) use single-unit placebo test (see section 2.3.1). In this test, the synthetic control method is applied to one control unit from all possible controls that the most resemble the Basque country before the terrorist activity. The evolution of the outcome variable of the “placebo-treated”, and its synthetic control followed almost the same path, which proved the small effect of the terrorist activity outside of Basque country.

Moreover, in order to check if the terrorism causes the GDP gap, Abadie and Gardeazabal (2003) look at the relationship between the per capita GDP gap (synthetic versus actual treated) and the intensity of the terrorism in the Basque country during the sample period. They use, what they call, the “impulse-response function” to construct confidence intervals and they prove by this test that the terrorist activity explains the GDP gap almost perfectly.

Abadie et al. (2010)

The article “Synthetic control methods for comparative case studies: Estimating the effect of California’s tobacco control program” by Abadie et al. (2010) is the second paper from the series on SCM. This article is built on the first article Abadie and Gardeazabal (2003) and examines the advantages of utilisation of SCM over traditional methods in comparative case studies. The authors propose a simple econometric model that also points out the preferences over traditional panel data or difference-in-differences estimators.

Moreover, they extend the single-unit placebo study (see Abadie and Gardeazabal (2003)) and propose a new inferential method to demonstrate the significance of their estimates. They put forward exact inferential techniques, so-called “in-space placebo” test (see section 2.3.1). The new method provides the ability to perform valid inferences on the effect of treatment independently from the number of available comparison units, the number of available time periods and whether aggregate or individual data are used for the analysis. They conclude that the potential application of SCM to comparative case studies is very large, especially in situations where traditional regression methods are not appropriate.

The empirical part of this paper concerns the application of the SCM to study the effect of California’s Proposition 99, a large-scale tobacco control program implemented in California in 1988. They used other states from the United States to construct the synthetic control unit. The results show a very significant decrease in tobacco consumption following the passing of Proposition 99, relative to a comparable synthetic control region. Besides, the estimates of Proposition 99 using synthetic control approach are considerably larger than those obtained by Fichtenberg and Glantz (2000) using linear regression method for the same study.

Abadie et al. (2015)

The article “Comparative politics and the synthetic control method” by Abadie et al. (2015) is the last paper in the series on synthetic control methods. The authors use the two previous papers on SCM[1] to discuss how this approach can be applied to complement comparative case studies in political science, as a way to bridge the qualitative and quantitative approaches to empirical research.

In particular, they promote the “in-time placebo” test (see section 2.3.1) as an inference mean in small-sample comparative studies. Beside the presentation of the placebo test, they implement the use of the root mean squared prediction error (see section 2.3.2) to prove the significance of the result. Finally, they also propose different sensitivity tests to show the robustness of the model built using the synthetic control method.

As a case study, they use the economic impact of the 1990 German reunification on West Germany. They use other OECD countries to produce the West Germany synthetic control. The study finds the negative effect of the reunification on economic growth in West Germany.

[1] Abadie and Gardeazabal (2003); Abadie et al. (2010).

Synthetic control method in others reviews

The first study using the synthetic control method was reported in 2003 (Abadie and Gardeazabal (2003)), but it is only the second article in 2010 (Abadie et al. (2010)), that initiated large expansion of its use. Since then, many studies employed SCM as a tool to evaluate the treatment effect. We will not enumerate these studies, but see Craig (2015, pp. 6-8) who presents a short review of synthetic control studies between 2003 to 2015.

2.2 Synthetic control methodology

In this section, we first introduce basics of the synthetic control method, as the notations, the driving model and its implementation. We follow by presenting different techniques to choose the optimal weights defining the synthetic control unit. And in the last part, we show few ways how to present the results of the analysis before running statistical inferences that are presented in chapter 2.3.

2.2.1 Basics

In order to run synthetic control method we suppose to collect the data on $J+1$ units indexed by $j=1,\ldots,J+1$. The data forms a balanced panel sample S, that is, no missing observations are present. Without loss of generality, we define that only the first unit $j=1$ is exposed to the treatment and is uninterruptedly exposed to the intervention of interest after some initial treatment period. This unit is described as treated (I)[2]. The rest of the units are the J potential controls (N)[3] that are not participating in the treatment and all of them constitute so-called "donor pool"[4]. Table 2.1 contains typical data set needed for the SCM analysis.

All the $J+1$ units are observed over T periods, indexed by $t=1,\ldots,T$. The time period is divided in two subsequent periods. We suppose a positive number of pre-treatment periods T_0, for $t=1,\ldots,T_0$, and a positive number of post-treatment periods T_1, for $t=T_0+1,\ldots,T$, with $T=T_0+T_1$ and $1 \leq T_0 < T$. This means that we do not have any interruption in observation and that there is at least one pre-treatment and one post-treatment period.

As already presented in section 1.2.1, the variable Y_{jt} is the potential outcome and measures the impact of the treatment. Y_{jt}^N is the outcome that would be observed for the unit j at time t in the absence of the treatment. Y_{jt}^I is the outcome that would be observed for unit j at time t if the unit is exposed to the treatment in period T_0+1 to T.

In addition to the outcome variable, we observe for each unit the confounding variables C^l, $l=1,\ldots,m$. The $(m \times T)$ matrix $\mathbf{C}_j$ contains m confounding variables C^l. As we will see later in this section, we use the confounding variables to build the vector of observed covariates $\mathbf{Z}$.

[2]The index I as intervention.
[3]The index N as non-intervention.
[4]The term donor pool is borrowed from medical terminology where it does describe the potential donors of the organs.

Unit	Identificator	Time		Outcome		Confounders		
j	NAME	t		$\mathbf{Y}$		C^1	$\cdots$	C^m
1	Treated	1	pre-treatment	Y_{11}	$\mathbf{Y}_1$	C^1_{11}	$\cdots$	C^m_{11}
		$\vdots$		$\vdots$		$\vdots$		$\vdots$
		T_0		Y_{1T_0}		$C^1_{1T_0}$		$C^m_{1T_0}$
		T_0+1	post-treatment	Y_{1T_0+1}		$C^1_{1T_0+1}$		$C^m_{1T_0+1}$
		$\vdots$		$\vdots$		$\vdots$		$\vdots$
		T		Y_{1T}		C^1_{1T}		C^m_{1T}
2	Control 1	1		Y_{21}	$\mathbf{Y}_2$	C^1_{21}	$\cdots$	C^m_{21}
		$\vdots$		$\vdots$		$\vdots$		$\vdots$
		T		Y_{2T}		C^1_{2T}		C^m_{2T}
$\vdots$	$\vdots$	$\vdots$		$\vdots$		$\vdots$	$\vdots$	$\vdots$
$J+1$	Control J	1		Y_{J+11}	$\mathbf{Y}_{J+1}$	C^1_{J+11}	$\cdots$	C^m_{J+11}
		$\vdots$		$\vdots$		$\vdots$		$\vdots$
		T		Y_{J+1T}		C^1_{J+1T}		C^m_{J+1T}

Source: Author's elaboration.

Table 2.1: Data set

Assumptions

As most of the program evaluation methods, the SCM is not an exception and is based on a couple of assumptions. The first assumption is defined as:

Assumption 4 (First SCM assumption)**.**

We presume that the intervention does not have any effect on pre-treatment outcome and so we have $Y^N_{jt} = Y^I_{jt}$ for all $t \in \{1,\dots,T_0\}$ and $j \in \{1,\dots,J+1\}$. Note that in practice the treatment may have been anticipated and the impact on the outcome is visible before the selected treatment period. In this case, we can eventually redefine T_0 as the first period in which the outcome may possible react to the treatment.

Furthermore, the second assumption on which is based the synthetic control method is defined as:

Assumption 5 (Second SCM assumption)**.**

We assume no interference between units (described in previous chapter by assumption 1 as SUTVA). That is, we suppose that the control units' outcomes are not affected by the treatment.

Treatment effect

We define by $\alpha_{jt} = Y_{jt}^{I} - Y_{jt}^{N}$ the effect of the treatment for unit j at time t. The treatment effect for any unit and time period is represented by the figure 2.1. Moreover, let D_{jt} be the causal exposure variable described in section 1.2.1. We know that only the first unit is exposed to the treatment after period T_0, consequently, the causal exposure variable is redefined as:

$$D_{jt} = \begin{cases} 1 & \text{if} \quad j = 1 \quad \text{and} \quad t > T_0, \\ 0 & \qquad \text{otherwise.} \end{cases} \tag{2.1}$$

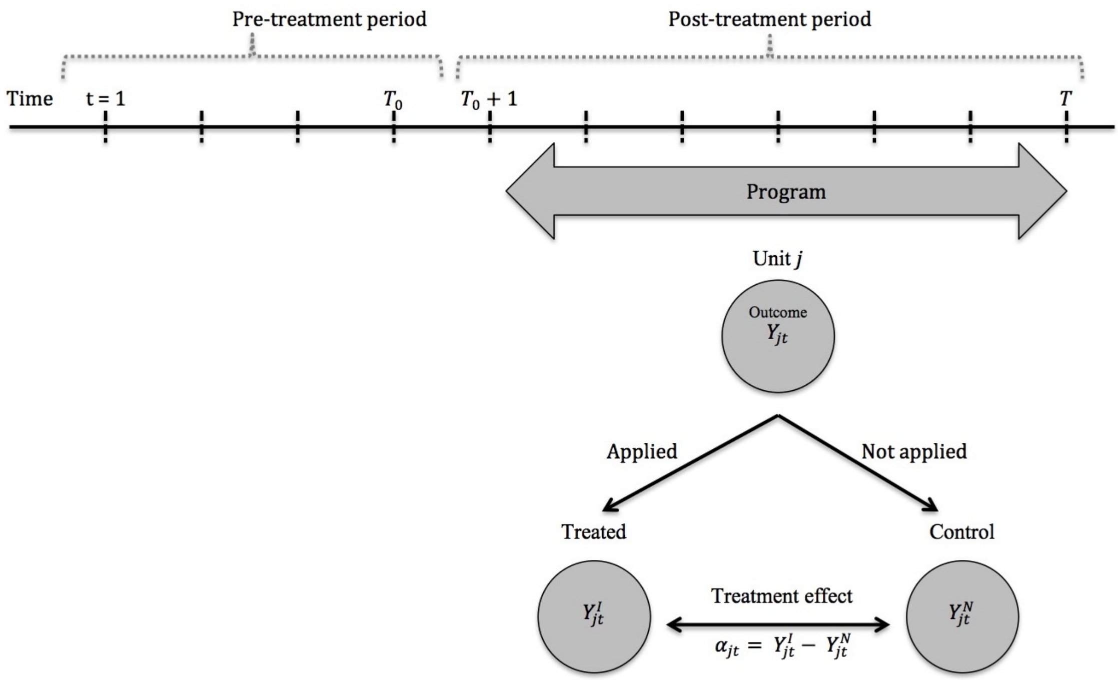
Therefore the observed outcome for unit j at time t is:

$$Y_{jt} = Y_{jt}^{N} + \alpha_{jt} \cdot D_{jt}. \tag{2.2}$$

As a result of equations (2.1) and (2.2), the treatment effect for unit $j = 1$ at time $t > T_0$ is defined as:

$$\alpha_{1t} = Y_{1t} - Y_{1t}^{N}. \tag{2.3}$$

Note that only the Y_{1t}^{N} is unobserved. The goal of the synthetic control method is to construct a synthetic control group providing an estimate for this missing potential outcome.



Source: Author's elaboration.

Figure 2.1: Treatment effect

Driving model

Synthetic control approach belongs to the class of difference-in-differences methods (for more details on the method see annexe A.1.1). It is a generalised DID (fixed-effect) model that allows the effect of confounding unobserved characteristics to vary over time. In order to estimate the potential outcome of non-treated unit, Y_{jt}^N, based on a specific factor model[5], Abadie et al. (2010) propose to use the weighted value of the outcome variable for each control from the donor pool that is:

$$\sum_{j=2}^{J+1} w_j Y_{jt},$$

where w_j is a value of the $(J \times 1)$ vector of weights $\mathbf{W} = (w_2, \dots, w_{J+1})'$, s.t $w_j \geq 0$ and $\sum_{j=2}^{J+1} w_j = 1$. Each scalar w_j represents the weight of unit j in the synthetic control. Each particular vector $\mathbf{W}$ generates one particular weighted average of control units, therefore one potential synthetic control. Ideally, we would like to choose among the set of all possible $\mathbf{W}$ a vector $\mathbf{W}^* = (w_2^*, \dots, w_{J+1}^*)'$ such that:

$$\sum_{j=2}^{J+1} w_j^* Y_{jt} = Y_{1t} \quad \text{and} \quad \sum_{j=2}^{J+1} w_j^* \mathbf{Z}_j = \mathbf{Z}_1, \quad \forall t \leq T_0. \tag{2.4}$$

Note that these conditions have to be true for all $t \leq T_0$, i.e. for all t in pre-treatment period. Moreover, if we ignore, for this moment, the mathematical optimisation procedure described in section 2.2.2, we can imagine the synthetic control matching procedure as a black box, and the results of it should be the set of weights $\mathbf{W}^*$. We represent the matching procedure graphically by figure 2.2. During the pre-treatment period, the treated unit $j = 1$ is looking for the units in the donor pool that has similar characteristics. The results of the matching are the combination of the control units that the most resembles the treated unit before the treatment. For more details about the matching see annexe A.1.1.

If we suppose that there is such $\mathbf{W}^*$ satisfying equations in (2.4), then under condition of no extrapolation outside the convex hull of the data[6], Abadie et al. (2010) suggest an estimator of treatment effect (see equation (2.3)), defined as:

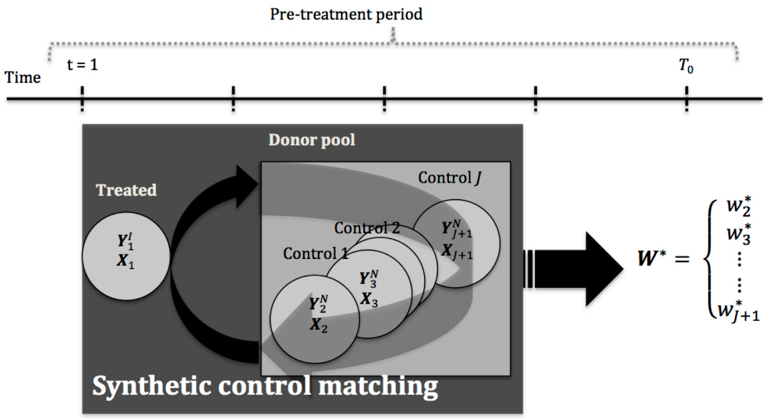
$$\hat{\alpha}_{1t} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt}, \quad \forall t > T_0. \tag{2.5}$$

Note that equations in (2.4) hold exactly if $(\mathbf{Z}_1', Y_{11}, \dots, Y_{1T_0})$ belongs to convex hull of $\{(\mathbf{Z}_2', Y_{21}, \dots, Y_{2T_0}), \dots, (\mathbf{Z}_{J+1}', Y_{J+11}, \dots, Y_{J+1T_0})\}$. In practice, these equalities often do not hold, hence we have to make sure that the synthetic control is selected such that the equations in (2.4) hold approximatively[7].

[5] For more explanation see Abadie et al. (2010, pp. 496).

[6] For the proof see Abadie et al. (2010, p. 504).

[7] In addition, if our treated unit is an outlier (extreme value), the $(\mathbf{Z}_1', Y_{11}, \dots, Y_{1T_0})$ is to far of the convex hull of $\{(\mathbf{Z}_2', Y_{21}, \dots, Y_{2T_0}), \dots, (\mathbf{Z}_{J+1}', Y_{J+11}, \dots, Y_{J+1T_0})\}$ so in this case the synthetic control would not provide a good matching.



Source: Author's elaboration.

Figure 2.2: Synthetic control matching

Abadie et al. (2010) argue that synthetic control can provide useful estimates also in more general context, for example, in the case of the autoregressive model with time-varying coefficients:

$$\begin{aligned} Y^N_{jt+1} &= \alpha_t Y^N_{jt} + \beta_{t+1}\mathbf{Z}_{jt+1} + u_{jt+1}, \\ \mathbf{Z}_{jt+1} &= \gamma_t Y^N_{jt} + \Pi_t \mathbf{Z}_{jt} + v_{jt+1}, \end{aligned}$$

where u_{jt+1} and v_{jt+1} have mean zero conditional on $\mathscr{F}_t = \{Y_{js}, \mathbf{Z}_{js}\}_{1\leq j\leq J+1, s\leq t}$. If we suppose that we can choose $\{w^*_j\}_{2\leq j\leq J+1}$ such that $\sum_{j=2}^{J+1} w^*_j Y_{jT_0} = Y_{1T_0}$ and $\sum_{j=2}^{J+1} w^*_j Z_{jT_0} = Z_{1T_0}$, then we can prove that the synthetic control estimator is unbiased even if only one pre-treatment period is available[8].

Implementation of the driving model

Ideally, we would like to construct a synthetic control that most closely resembles the treated unit in all relevant pre-treatment characteristics. To do so, Abadie and Gardeazabal (2003) propose to make use of the observed characteristics of the units from the donor pool. They also propose to weight the pre-treatment outcomes and form linear combinations of these outcomes to control for unobserved common factors whose effects vary over time. Abadie and Gardeazabal (2003), and Abadie et al. (2010) argue that if the pre-treatment period is large, then matching on pre-treatment outcomes helps control for unobserved factor and the heterogeneity of the effect of the observed and unobserved factors on the outcome of interest. Moreover, they specify that only units that are alike in both observed and unobserved determinants of the outcome variables as well as in the

[8]For the proof see Abadie et al. (2010, p. 504).

effect of those determinants on the outcome variables should produce similar trajectories of the outcome variable over an extended period.

In order to construct the synthetic control, we define the variables described in following paragraphs. Let $\mathbf{Z}_j = (Z_j^{\mathbf{L}_1}, \ldots, Z_j^{\mathbf{L}_i}, \ldots, Z_j^{\mathbf{L}_r})'$ be a vector of predictors of the outcome variables that are not affected by the treatment. To be more specific, let $\mathbf{C}_j$ be $(m \times T)$ matrix containing observations of confounding variables C^l, $l = 1, \ldots, m$, for T periods. Each $Z_j^{\mathbf{L}_i}$ is a linear combination of some confounding variable C^l[9].

We also define $\mathbf{K} = (k_1, \ldots, k_{T_0})'$, a $(T_0 \times 1)$ vector that denotes some linear combination of pre-treatment outcomes, $Y_j^{\mathbf{K}} = \sum_{s=1}^{T_0} k_s Y_{js}$[10]. We consider till maximum $M \leq T_0$ of such linear combinations defined by the vectors $\mathbf{K}_1, \ldots, \mathbf{K}_M$[11].

In addition, let $\mathbf{X}_1 = (\mathbf{Z}'_1, Y_1^{\mathbf{K}_1}, \ldots, Y_1^{\mathbf{K}_M})'$ be a vector of pre-treatment characteristics for the unaffected unit, with $k = r + M$ column. And $\mathbf{X_0}$, $(k \times J)$ matrix of pre-treatment values predictors for the J control units with j-th column equals to $(\mathbf{Z}'_j, Y_j^{\mathbf{K}_1}, \ldots, Y_j^{\mathbf{K}_M})'$. The values of the predictor variables reflect the heterogeneity between the units. The vector $\mathbf{X}_1$ and the matrix $\mathbf{X}_0$ are presented as follow:

$$\mathbf{X_1} = \begin{bmatrix} Z_1^{\mathbf{L}_1} \\ \vdots \\ Z_1^{\mathbf{L}_r} \\ Y_1^{\mathbf{K}_1} \\ \vdots \\ Y_1^{\mathbf{K}_M} \end{bmatrix}; \qquad \mathbf{X_0} = \begin{bmatrix} Z_2^{\mathbf{L}_1} & \cdots & Z_j^{\mathbf{L}_1} & \cdots & Z_{J+1}^{\mathbf{L}_1} \\ \vdots & \cdots & \vdots & \cdots & \vdots \\ Z_2^{\mathbf{L}_r} & \cdots & Z_j^{\mathbf{L}_r} & \cdots & Z_{J+1}^{\mathbf{L}_r} \\ Y_2^{\mathbf{K}_1} & \cdots & Y_j^{\mathbf{K}_1} & \cdots & Y_{J+1}^{\mathbf{K}_1} \\ \vdots & \cdots & \vdots & \cdots & \vdots \\ Y_2^{\mathbf{K}_M} & \cdots & Y_j^{\mathbf{K}_M} & \cdots & Y_{J+1}^{\mathbf{K}_M} \end{bmatrix}. \tag{2.6}$$

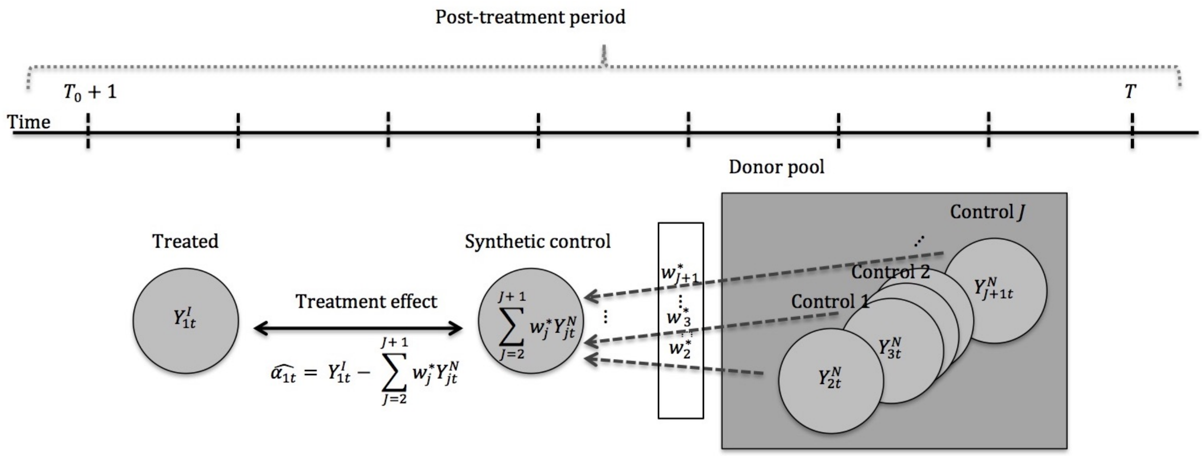
Note that the choice of the predictor variables in $\mathbf{X}$ is very important. The values of the predictor variables reflect the heterogeneity between the units. We should make sure that we chose the variables that have a good predictive power of the potential outcome variable, but that they are not affected by the treatment. Moreover, it is crucial that synthetic control closely reproduces the values of the variables with a large predictive power on the outcome of interest.

Final step before the estimation process is to define a $(J \times 1)$ vector of weights $\mathbf{W} = (w_2, \ldots, w_{J+1})'$ such that $0 \leq w_j \leq 1$, for $j = 2, \ldots, J+1$, and $\sum_{j=2}^{J+1} w_j = 1$.

[9] We define $\mathbf{L} = (l_1, \ldots, l_{T_0})'$,a $(T_0 \times 1)$ vector that denotes some linear combination of pre-treatment confounding covariates, $Z_j^{\mathbf{L}} = \sum_{s=1}^{T_0} l_s C_{js}$. Natural choice is to take average of all pre-treatment observations, but other choices are also possible.

[10] Abadie et al. (2010) propose different possibilities to choose $Y_j^{\mathbf{K}}$. First choice is to take the value of the outcome variable in the period immediately prior to the treatment, that is $k_1 = k_2 = \ldots = k_{T_0-1} = 0$, $k_{T_0} = 1$ and $Y_j^{\mathbf{K}} = Y_{jT_0}$. Second option is to take simple average of the outcome variable for the pre-treatment periods, that is $k_1 = k_2 = \ldots = k_{T_0} = 1/T_0$ and $Y_j^{\mathbf{K}} = T_0^{-1} \sum_{s=1}^{T_0} Y_{js}$.

[11] One intuitive choice for M linear combinations of pre-treatment outcomes is to take all available pre-treatment periods, that is $Y_j^{\mathbf{K}_1} = Y_{j1}, \ldots, Y_j^{\mathbf{K}_M} = Y_{jT_0}$. In practice we consider only few linear combinations of pre-treatment outcomes and check whether equation (2.4) holds approximatively.



Source: Author's elaboration.

Figure 2.3: Treatment effect estimation

The estimate of the treatment effect, $\hat{\alpha}_{it}$, was defined in equation (2.5), where $\sum_{j=2}^{J+1} w_j^* \mathbf{Y}_{jt}$ estimates the unobserved counterfactual outcome Y_{1t}^N. The treatment effect estimation is represented by figure 2.3. In order to find the estimate of Y_{1t}^N, we choose a vector $\mathbf{W}^* = (w_2^*, \ldots, w_{J+1}^*)'$ such that the resulting synthetic control best approximates the unit exposed to the intervention with respect to the outcome predictors $\mathbf{Z}$ and M linear combinations of pre-treatment outcome $Y_j^{K_1}, \ldots, Y_j^{K_M}$. In other words, we seek $\mathbf{W}^*$ that satisfy the following equations:

$$\sum_{j=2}^{J+1} w_j^* Y_j^{\mathbf{K}} = Y_1^{\mathbf{K}} \quad \text{and} \quad \sum_{j=2}^{J+1} w_j^* \mathbf{Z}_j = \mathbf{Z}_1. \tag{2.7}$$

In general, we cannot find $\mathbf{W}^*$ such that the equations in (2.7) hold exactly. Thus, we try to make the difference between the characteristics of the treated unit and its synthetic control as small as possible. Note that this difference is given by $\mathbf{X}_1 - \mathbf{X}_0\mathbf{W}$. Following Abadie et al. (2010) we select the synthetic control, $\mathbf{W}^*$, that minimise the distance:

$$\|\mathbf{X}_1 - \mathbf{X}_0\mathbf{W}\|_{\mathbf{V}} = \sqrt{(\mathbf{X}_1 - \mathbf{X}_0\mathbf{W})'\mathbf{V}(\mathbf{X}_1 - \mathbf{X}_0\mathbf{W})}, \tag{2.8}$$

subject to $0 \le w_j \le 1, j = 2, \ldots, J+1$ and $\sum_{j=2}^{J+1} w_j = 1$, where $\mathbf{V}$ is some $(k \times k)$ symmetric and positive semidefinite matrix (other choices are also possible). The diagonal elements in $\mathbf{V}$ are weights which reflect the relative importance of the variables in $\mathbf{X}_0$ and $\mathbf{X}_1$.

A couple of remarks has to be done. The first one is that even though the synthetic control is defined as convex combinations of control units, negative weight or weights larger than one can be used at the cost of allowing extrapolation. The second one concerns a penalty terms included in the estimation to reduce the interpolation bias. On that problematic Abadie et al. (2010, p. 496) specify: *"If the relationship between the outcome variable and the explanatory variables in* $\mathbf{X}_1$ *and* $\mathbf{X}_0$ *is highly nonlinear and the support of the explanatory variables is large, interpolation bias may be severe. In that case,* $\mathbf{W}^*$ *can be chosen to minimise the distance* $\|\mathbf{X}_1 - \mathbf{X}_0\mathbf{W}\|$ *plus a set of* *penalty terms specified as increasing function of the distance between $\mathbf{X}_1$ and the corresponding value for the units with positive weights in $\mathbf{W}$. Alternatively, interpolation bias can be reduced by restricting the comparison group to units that are similar to the exposed units in term of the values of $\mathbf{X}_1$.*" Though, it is recommended to restrict the donor pool to units with outcomes that are thought to be driven by the same structural process as the treated unit.

Note that the weight for the synthetic control $\mathbf{W}^*$ is a function of $\mathbf{V}$. Hence the optimal choice of $\mathbf{W}$ is dependent on the weighting matrix $\mathbf{V}$. Abadie and Gardeazabal (2003), and Abadie et al. (2010) propose different option of choosing $\mathbf{V}$, described in the following section 2.2.2.

2.2.2 Optimal choice of $\mathbf{V}$

The matrix $\mathbf{V}$ is introduced to the model in order to allow different weights to the variables in $\mathbf{X}_0$ and $\mathbf{X}_1$ depending on their predictive power on the outcome. There are different possibilities of choosing $\mathbf{V}$. The first one is base on subjective assessments of the predictive power of the variables in $\mathbf{X}$. More the variable has the influence on the path of the outcome variable, bigger is its weight in the matrix. The second one is data-driven procedure[12]. In this method, we choose $\mathbf{V}$ such that the difference of pre-treatment outcome of the treated unit and its synthetic counterpart is minimised. The last method is cross-validation. This method is based on the data-driven procedure but uses two pre-treatment periods to find $\mathbf{V}$. The data-driven and cross-validation procedures are explained in the following sections.

Data-driven procedure

The choice of $\mathbf{V} = diag(v_1, \dots, v_k)$ influences the mean squared error of the synthetic control estimator. Abadie and Gardeazabal (2003), and Abadie et al. (2010) argue that the optimal choice of $\mathbf{V}$ assigns weights that minimise the mean squared error of the estimator. In other words, we choose $\mathbf{V}^*$ among all positive definite and diagonal matrices such that the mean squared prediction error of the outcome variable is minimised over some set of pre-treatment periods, T_p[13] with $(1 \leq T_p \leq T_0)$. The minimisation problem translates to the following equation:

$$\arg\min_{V \in \mathbb{V}} (\mathbf{U}_1 - \mathbf{U}_0\mathbf{W}^*(\mathbf{V}))'(\mathbf{U}_1 - \mathbf{U}_0\mathbf{W}^*(\mathbf{V})), \tag{2.9}$$

where U_1 is a $(T_p \times 1)$ vector containing values of Y_1 for some set of pre-treatment periods, U_0 is a $(T_p \times J)$ matrix with values of Y_0 for some set of pre-treatment periods, $\mathbb{V}$ is the set of all nonnegative diagonal $(k \times k)$ matrices and $\mathbf{W}^* = \mathbf{W}^*(\mathbf{V})$ are weights for some possible synthetic control. The objective is to find $\mathbf{W}^* = \mathbf{W}^*(\mathbf{V}^*)$, that is the optimal weights for the synthetic control, that we can obtain by classical nested optimisation problem[14] where we minimise equation (2.9),

[12] The three articles, Abadie and Gardeazabal (2003); Abadie et al. (2010, 2015), defend the use of the data-driven procedure to produce the comparison unit.

[13] Natural choice is $T_p = T_0$, so the $\mathbf{V}^*$ minimises the mean squared prediction error over the entire pre-treatment period. Often it is sufficient to chose $T_p < T_0$ to achieve a low MSPE over the entire pre-treatment period.

[14] Nested optimisation is special kind of optimisation when one problem is embedded (nested) within another.

for $\mathbf{W}^*$ resulting from the minimal distance given in equation (2.8). Moreover, note that Abadie and Gardeazabal (2003) recommend to normalise the Euclidean norm of $\mathbf{V}^*$ (i.e. $diag(\mathbf{V}^*)$ to one, as there are infinitely many equivalent solutions for $\mathbf{V}^*$.

Alternatively to this nested optimisation, the synthetic control could take into consideration only the pre-treatment outcome, and so we try to find $\mathbf{W}^*$ such that:

$$\arg\min_{W \in \mathbb{W}} (\mathbf{U}_1 - \mathbf{U}_0\mathbf{W}^*)'(\mathbf{U}_1 - \mathbf{U}_0\mathbf{W}^*), \tag{2.10}$$

where $\mathbb{W} = \{(w_1, \dots, w_J)'$ subject to $0 \leq w_j \leq 1, j = 2, \dots, J+1$ and $\sum_{j=2}^{J+1} w_j = 1\}$.

It is often the case that the synthetic control derived by equation (2.10) produces larger treatment effect than the one taking into account also the potential outcome predictors (the first optimisation problem). This alternative optimisation does not take into account different characteristics of each unit. Thus the respective synthetic control may not be fully representative of the treated unit. Consequently, if we possessed data containing predictors with good predictive power, the first optimisation that we presented in this section would be a preferable option in order to find optimal weights.

Cross-validation method

If the number of available pre-treatment periods in the sample is large enough, we may use the cross-validation method to find the matrix $\mathbf{V}$. In this approach we divide the pre-treatment period into an initial training periods, T_{P_1}, and a subsequent validation period, T_V, with $1 \leq T_{P_1} < T_V \leq T_0$.

Given a $\mathbf{V}$, we compute $\mathbf{W}^*(\mathbf{V})$ using data from the training period. Then, the matrix $\mathbf{V}$ can be chosen to minimise the mean squared prediction error of $\mathbf{W}^*(\mathbf{V})$ from the validation period. In certain way, the cross-validation method is an alternative application of data-driven procedure. In other words, we minimise equation (2.9) over the validation period, T_V, for $\mathbf{W}^*(\mathbf{V})$ given in equation (2.8) minimised over the training period, T_{P_1}.

Note that, this method requires a substantial number of pre-treatment periods. Abadie et al. (2015) do not recommend using this method when the pre-treatment fit is poor (see section 2.3.2) or the number of pre-treatment periods is small.

2.2.3 How to present some analysis' results

The results of the synthetic control analysis can be presented as tables (see tables 2.2-2.5) or graphs (see figure 2.4). Note that in this section we present only a generic pattern of results for the treated unit. The inference tests are presented in the following chapter 2.3.

Quantitative results

The first aspect of the analysis we might want to check is the relative contribution of each control unit to the synthetic control. The table 2.2 shows the values of the optimal weight for the synthetic control. The control unit j from the donor pool is weighted by the weight w_j^*. Remind that all the weights should be positive, and the sum of the weights is equal to one. Bigger is the w_j^*, more important is the respective control unit in the synthetic control.

Another element to examine could be the relative contribution of each predictor to the synthetic control. Table 2.3 presents the weights v_i reflecting the relative importance of the variables in X_0 and X_1. We apply the same condition as for the control units of no extrapolation outside of the convex hull, that is $0 \leq v_i \leq 1, i = 1,\ldots,k$ and $\sum_{i=1}^{k} v_i = 1$. At the optimum, we note v_i by v_i^*. As previously, the bigger is the v_i^*, the more influence has the respective predictor. Note that it could be that some predictors have very small contribution in the synthetic control. There are three reasons for that. It is either because the treated and control units are very similar with respect to the specific characteristic. The second reason could be that the treated unit outperforms the control units regarding the relative predictor[15]. And the last reason is that other predictors have simply much bigger predictive power than the one with a small contribution. Closer analysis of the respective weights is always very important.

Third table 2.4 shows the treatment effects $\hat{\alpha}_{1t}$ defined in equation (2.5). Note that in this table the treatment effect is defined for all periods and not only for the post-treatment period as defined in the equation (2.5). The treatment effects between the treated and its synthetic control should be close to zero during the pre-treatment period, that is, there is no difference between the treated unit and its synthetic control. On the other side, if we expect a positive or negative treatment effect, the treatment effect should be different from zero in the post-treatment period. The size of the effect is very arbitrary and depends on each case individually. Alternatively, we might want to calculate the average treatment effect for a set of periods by:

$$\hat{\hat{\alpha}} = \frac{1}{n_t} \sum_{t=t_1}^{t_2} \hat{\alpha}_{1t}, \tag{2.11}$$

where t_1 and t_2 are the periods for which we want to calculate the average treatment effect, and n_t is the number of the respective periods. Eventually, we can also associate different weights to each period if we judge that distinct years do have non-identical importance in the estimation (e.g., first years of the program might have more importance for the treatment effect that the last years).

Similar to the matching estimators, the synthetic control method demonstrates the affinity between the treated unit and its synthetic counterpart. These affinities are shown in table 2.5. The second column represents the value of the predictor for the treated units, respectively the values of $Y_1^{\mathbf{K}}$ and $\mathbf{Z}_1$ from equations (2.7). The third column of the table presents values of the synthetic control unit predictors, that is the values of $\mathbf{X}_0\mathbf{W}^*$ (respectively $\sum_{j=2}^{J+1} w_j^* Y_j^{\mathbf{K}}$ and $\sum_{j=2}^{J+1} w_j^* \mathbf{Z}_j$). By comparing these two columns, we check how well the weighted combination of the control units reproduces the values of outcome predictors before the treatment. In other words, we verify the

[15] For example, one company that participates in the certain program has extremely big revenue with respect to the other companies, which do not participate to the program.

equality of the equations in (2.7). Additionally, we can also compare the results to the last column of the table which contains the values of the sample means for the predictors, respectively $\frac{1}{J}\sum_{j=2}^{J+1}\mathbf{Z}_j$ and $\frac{1}{J}\sum_{j=2}^{J+1}Y_j^{\mathbf{K}}$. The comparison of all columns would give an idea how well the synthetic control outperforms the averages, as we have seen in the first chapter that the simple comparison of the expected values is a common way to set and evaluate the treatment effect.

Table 2.2: Control units' weights

Unit name	w weight
Control 1	w_2^*
$\vdots$	$\vdots$
Control i	w_i^*
$\vdots$	$\vdots$
Control J	w_{J+1}^*

Table 2.3: Predictors' weights

Predictor	v weight	
Z^1	v_1^*	predictors
$\vdots$	$\vdots$	
Z^r	v_r^*	
$Y^{\mathbf{K}_1}$	v_{r+1}^*	special predictors
$\vdots$	$\vdots$	
$Y^{\mathbf{K}_M}$	v_k^*	

Table 2.4: Treatment effects

Period	Gaps	
1	g_{11}	pre-treatment
$\vdots$	$\vdots$	
T_0	g_{1T_0}	
T_0+1	g_{1T_0+1}	post-treatment
$\vdots$	$\vdots$	
T	g_{1T}	

Table 2.5: Predictors

Predictor	Treated	Synthetic	Mean
Z^1	Z_1^1	Z^{1*}	$\bar{Z}^1$
$\vdots$	$\vdots$	$\vdots$	$\vdots$
Z^r	Z_1^r	Z^{r*}	$\bar{Z}^r$
$Y^{\mathbf{K}_1}$	$Y_1^{\mathbf{K}_1}$	$Y^{\mathbf{K}_1*}$	$\bar{Y}^{\mathbf{K}_1}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$
$Y^{\mathbf{K}_r}$	$Y_1^{\mathbf{K}_r}$	$Y^{\mathbf{K}_r*}$	$\bar{Y}^{\mathbf{K}_r}$

Source: Author's elaboration.

Table 2.6: Different synthetic control method results representations

Graphics

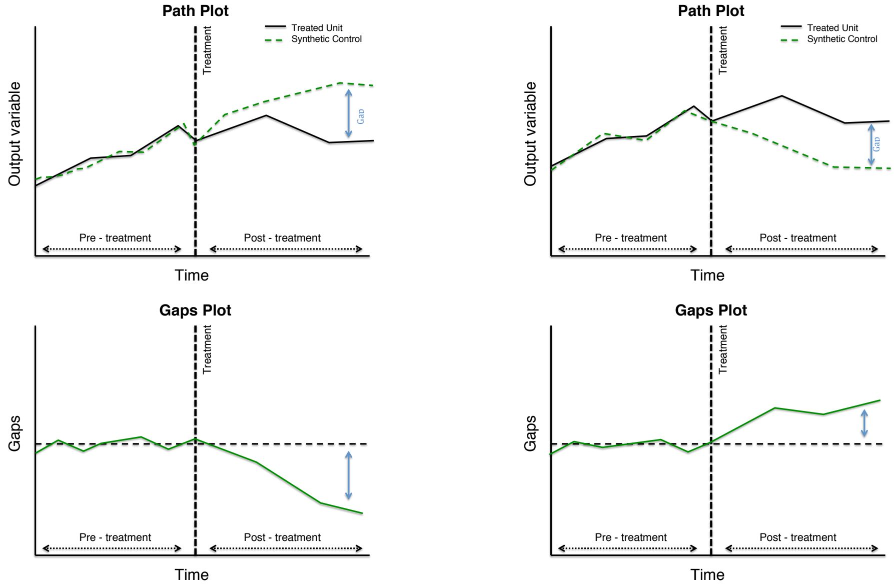
Note that the treatment effect can also be represented by the path plot or gaps plot (e.g., figure 2.4). The path plot, which is always the first plot in each quadrant, shows the values of the outcome variable for the treated unit Y_{1t}, represented by a black line and its synthetic control, $\sum_{j=2}^{J+1}w_j^*Y_{jt}$ represented by the dotted line. Gaps plot, the second graph in each quadrant, shows the values of the treatment effect reported from table 2.4. The horizontal dotted line in the gaps plot represent the zero treatment effect, and the vertical dotted line on both path' and gaps plots, represents the period when the treatment started. Figure 2.4 represents four different possible results of the analysis. In the following paragraphs, we have a closer look on each of the four figures.

The path and gaps plots on the figure 2.4a and 2.4b show treatment effect with negative values and treatment effect with positive values respectively. Before the treatment, during all pre-treatment period, there is the almost parallel evolution of treated unit and its synthetic control on the path plot. On the gaps plot, this is represented by the gaps line being as close as possible to the zero gap line. After the treatment, the both path plots show the deviation between the treated unit and its synthetic control. The figure 2.4a shows negative values of the treatment effect, so that the synthetic control lays above the treated unit on the path plot which is represented by a negative gap on the gaps plot. The opposite is true for the figure representing the positive values of the treatment effect. Note that positive values might mean a negative treatment effect and vice-versa (e.g. the increasing cost of goods sold after the introduction of cost reducing politics could be perceived as negative treatment effect or respectively no-effect).

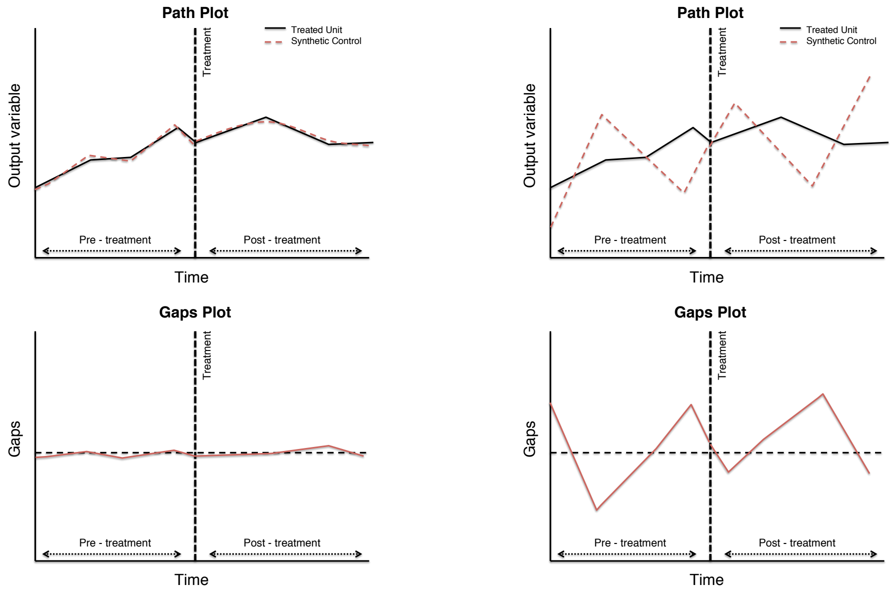
The path and gaps plot on the figure 2.4c shows a good match between the treated and control units during the pre-treatment period, which is a needed result after running the SCM. We explained the notion of a good match in the previous paragraph. The almost parallel evolution between the treated and synthetic control after the treatment (respectively no gap on the gaps plot), is representative for no treatment effect.

An example of a bad match between the treated unit and its synthetic control is shown on the path and gaps plot on the figure 2.4d. This is represented by no parallel path of the treated unit and its synthetic control on the path plot and unevenly distributed gaps around the zero gap line on the gaps plot. If there is no good match in the pre-treatment period, it is very likely that the no match continues in the post-treatment period too, as we represented it on the figures. In this case, the synthetic control does not provide good tools to find the treatment effect and the treated unit should not have to be considered in the analysis.

The figure 2.5 summarises the previous results of all graphs from the figure 2.4 with respect to the treatment effect and its graphical representation on the path plot. The green line that contours the zero gap line during the pre-treatment period signalise a good match between the treated unit and its synthetic control. On the other side, the red line in the pre-treatment period shows no match between the treatment and synthetic control. If we check the post-treatment period, the green line that goes up shows positive values treatment effect and the decreasing green line represents negative values treatment effect. The red line that contour the zero treatment effect line is this time signalling no treatment effect, as the gap between the treated and synthetic control unit is almost zero.



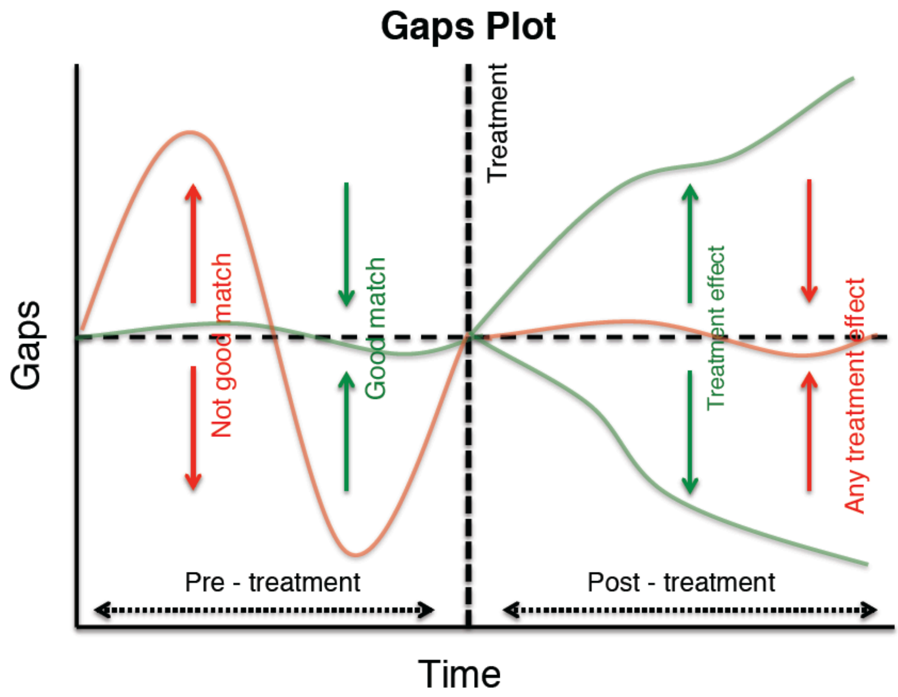
(a) Treatment effect with negative values (b) Treatment effect with positive values



(c) No effect (d) Bad match

Source: Author's elaboration.

Figure 2.4: Different examples of path and gaps plots



Source: Author's elaboration.

Figure 2.5: Gaps graph

2.2.4 Advantages and limitations of the synthetic control method

The SCM model has several advantages over the traditional regression and difference-in-differences methods. They are reviewed in Abadie et al. (2010). In this model we can minimise the biases caused by interpolating across units with very different characteristics by restricting the sample of units with $(\bar{Y}_j^K, \mathbf{Z}_j)$ sufficiently close to $(\bar{Y}_1^K, \mathbf{Z}_1)$ under some distance metric. That is, the control units we choose to put in a donor pool should be relatively similar to the treated unit. Inter alia, in contrast with the traditional DID this model allows the effect of confounding unobserved characteristics to vary over time. We should also add the transparency and safeguard against extrapolation. That is, we can see the relative contribution of each control unit to the synthetic control and the similarities between synthetic control and treated units in term of predictors and outcome. In addition, because the choice of synthetic control does not require access to post-treatment outcomes, the SCM allows deciding on study design without knowing how those decisions will affect the conclusions of their studies. In addition the SCM deals with the Omitted Variable Bias (OVB)[16] and the so-called "bad control"[17].

[16] See definition A.1.

[17] Angrist and Pischke (2008, pp. 47-51) elaborate the notion of bad control: *"Some variables are bad controls and should not be included in a regression model even when their inclusion might be expected to change the short regression coefficients. Bad controls are variables that are themselves outcome variables in the national experiment at hand. That is, bad controls might just as well be dependent variables too."*

A couple of limitations have to be mentioned. Abadie et al. (2015) argue different limits of the SCM. First, the credibility of the synthetic control depends upon how well it tracks the treated unit's characteristics and outcomes over an extended period of time prior to the treatment. They point out that as long as the synthetic control cannot reproduce exactly the characteristics of the treated unit before the treatment, the gap may have been created by differences in predictors between the treated unit and its synthetic control before the treatment, or by other differences not reflected by the data. Second, a substantial number of post-treatment periods may also be required in case when the effect of the intervention emerge gradually after the intervention or changes over time.

2.3 Statistical inferences

The use of statistical inference in comparative case studies is difficult because of the small sample nature of the data, the absence of randomisation or lack of a probabilistic sampling to select sample units. These limitations complicate the application of traditional approaches to statistical inference[18]. In addition, Abadie et al. (2010, pp. 496-497) say about the uncertainty in the comparative case studies: *"The standard error commonly used in regression-based comparative case studies measures uncertainty about aggregate data. However, perfect knowledge of aggregate data does not eliminate all uncertainty about the parameters of interest. In comparative case studies, an additional source of uncertainty derives from ignorance about the ability of the control group to reproduce the counterfactual of how the treated unit would have evolved in the absence of the treatment. This type of uncertainty is present regardless of whether aggregate data are used for estimation or not. The use of the individual data only increases the amount of uncertainty."*

Synthetic control method provides a way for an alternative mode of qualitative and quantitative inference. The synthetic control method systemises the process of estimating the counterfactuals and enables us not only to conduct falsification exercises, so-called "placebo studies", but also measure and test the misspecification of the model by the use of the root mean squared prediction error (Root Mean Squared Prediction Error (RMSPE)). Moreover, we can also carry out sensitivity analyses and robustness tests to amplify the veracity of our results. The use of the tests depends on the context, the number of the control units and the size of the observation period.

What do we test? The main question is about the gap between the observed outcome of the treated unit and estimated outcome of its synthetic control. We need to explain whether the gap accounts for the treatment, or is produced by different factors other than the treatment. Other important questions may arise during the analysis. For example, we may want to test the predictive power of the covariates on the outcome path. Besides, we may be interested in the matching goodness between treated unit and its synthetic control. Or we may be concerned by the robustness of our model to the number of units or variables. Next three sections describe different possibilities of running inferences in the synthetic control context. We explain the implementation of placebo tests, the use of the root mean squared prediction error, and introduce some possible robustness tests.

[18] Rubin (1990b) describes different modes of inferential statistics for causal effect.

2.3.1 Placebo tests

As already mentioned, the synthetic control method systematises the process of estimating the counterfactuals and enables to conduct placebo studies. Same as the term "donor pool", the designation "placebo" study comes from the medical terminology describing: *"a beneficial effect produced by a placebo drug or treatment, which cannot be attributed to the properties of the placebo itself, and must therefore be due to the patient's belief in that treatment [Oxford Dictionaries]."* In our case, the main idea of placebo studies is to predict the counterfactual outcome path for the units in the donor pool. That is, the units that did not receive the treatment and should not be affected by it, as described by the second SCM assumption (assumption 5).

This alternative model of inference is supported by the confidence that we have in the treatment effect produced by the synthetic control estimate. We assume that the treatment effect estimated for the unit that did or do participate in the program reflects the impact of the intervention. Replication of synthetic control analysis for the units that are not part of the program should not generate a significant divergence between synthetic and actual outcomes. This means that for the control units we should not obtain estimated effects of similar or even greater magnitude compared to the cases for which the treatment did take place. In this section, we present different variations of placebo tests, namely single-unit placebo, in-time placebo and in-space placebo tests.

An important remark regarding the placebo test methods is that they do not produce confidence intervals or posterior distributions, and the inferential exercise, including associated p-values, are restricted to the question of whether or not the estimated effect of the actual treatment is large relative to the distribution of placebo effects. Note also, that we can apply an exclusion rule to select the number of the units included in the calculation of the p-value. This rule is based on the root mean squared prediction error and is explained in the section 2.3.2.

Single-unit placebo

The first kind of placebo test is the so-called "single-unit placebo", where we apply the synthetic control method to one particular control unit from the donor pool. It is particularly helpful if there is only one or two control units that have a major contribution in the synthetic control. The test is based on the following recommendation:

Recommendation 1.

In the single-unit placebo test, if the "placebo-treated" unit (control unit being analysed as if it would have received the treatment) shows similar or even larger treatment effect than the "actual treated" unit (true treated unit), one has to reconsider the veracity of our results.

Significant evidence and interpretation

This test is purely visual, and we cannot calculate the p-value as for the in-space placebo one. In order to validate the significant treatment effect of the treated unit, we would like to observe: 1) similar plots to ones represented by figure 2.4a or 2.4b for the treated unit – perfect match before the treatment and positive or negative treatment effect; 2) similar plots to ones represented by figure 2.4c for the placebo-treated – perfect match before the treatment and no effect observed after the treatment (note that the synthetic control on the path plot 2.4c represents the placebo-treated unit). If the single unit placebo test create gaps of a magnitude similar to the one estimated for the treated, then the analysis does not provide significant evidence of a treatment effect for the treated unit.

This test can also catch an eventual "artificial" amplification of the treatment effect. That is, the placebo-treated shows an unusual deviation during a particular period. A good example is in Abadie and Gardeazabal (2003), where there was an increase in GDP during the Olympic games in Spain in 1992, and this external shock is not related to the treatment. Though, if we detect an unexpected behaviour of the outcome path, we need to do the qualitative research in order to explain this deviation.

The single-unit test can also apprehend the spillover effect (Abadie et al. (2015, p. 504)), that is the contamination of the donor pool by the treatment. This means that the SUTVA assumption is violated and that the treatment has an effect on other units than the treated. Notice that the limited number of units in the synthetic control allows the evaluation of the existence and direction of potential biases created by spillover effects. Though, if we suspect a potential interaction between the units, we should make a closer analyse and eventually reconsider the donor pool or introduce a punishment weight into the $\mathbf{W}^*$ matrix for the suspected units.

Note that Abadie and Gardeazabal (2003) recommend to keep out the actual treatment unit from the "placebo" donor pool. This recommendation is especially valid if we know that the treated and placebo treated units are similar in observed and latent predictor and characteristics.

In-time placebo

In the case of the number of available comparison units is very small, and the pre-treatment time period is relatively long, covering at least several years, we can use the longitudinal dimension of the data to produce placebo studies. Abadie et al. (2015) present and apply so-called "in-time placebo test". The test is based on the following recommendation:

Recommendation 2.

The validity of the result would be dissipated if the synthetic control method also estimates large effects when applied to periods when the treatment did not take place.

Note that this recommendation is based on the first SCM assumption (assumption 4). To build the test, we process as follows. We select a random period in the pre-treatment period, $\hat{T}_0 + 1$, and suppose that the treatment started at $\hat{T}_0$ instead of the real first treatment period $T_0 + 1$. Then we analyse if there was or not a treatment effect for the date where the treatment did not take place. In this way, the in-time placebo is similar to the single-unit placebo, with the difference that we use the "placebo date" instead of "placebo-treated" unit. The test has a similar interpretation.

Significant evidence and interpretation

In order to validate the significant treatment effect of the treated unit, we would like to observe similar plots to the ones represented by figure 2.4a or 2.4b for the treated unit when the true post-treatment period is applied, and the plots on the figure 2.4c for the treated unit when the random pre-treatment period is selected as the first treatment period (note that the treatment vertical line on the graph 2.4c represents the beginning of the "placebo treatment" $\hat{T}_0 + 1$). If the in-time placebo test creates gaps of the magnitude similar to the one estimated for the treated unit when applied to the right dates, then the analysis does not provide significant evidence of a treatment effect for the treated unit.

In-space placebo

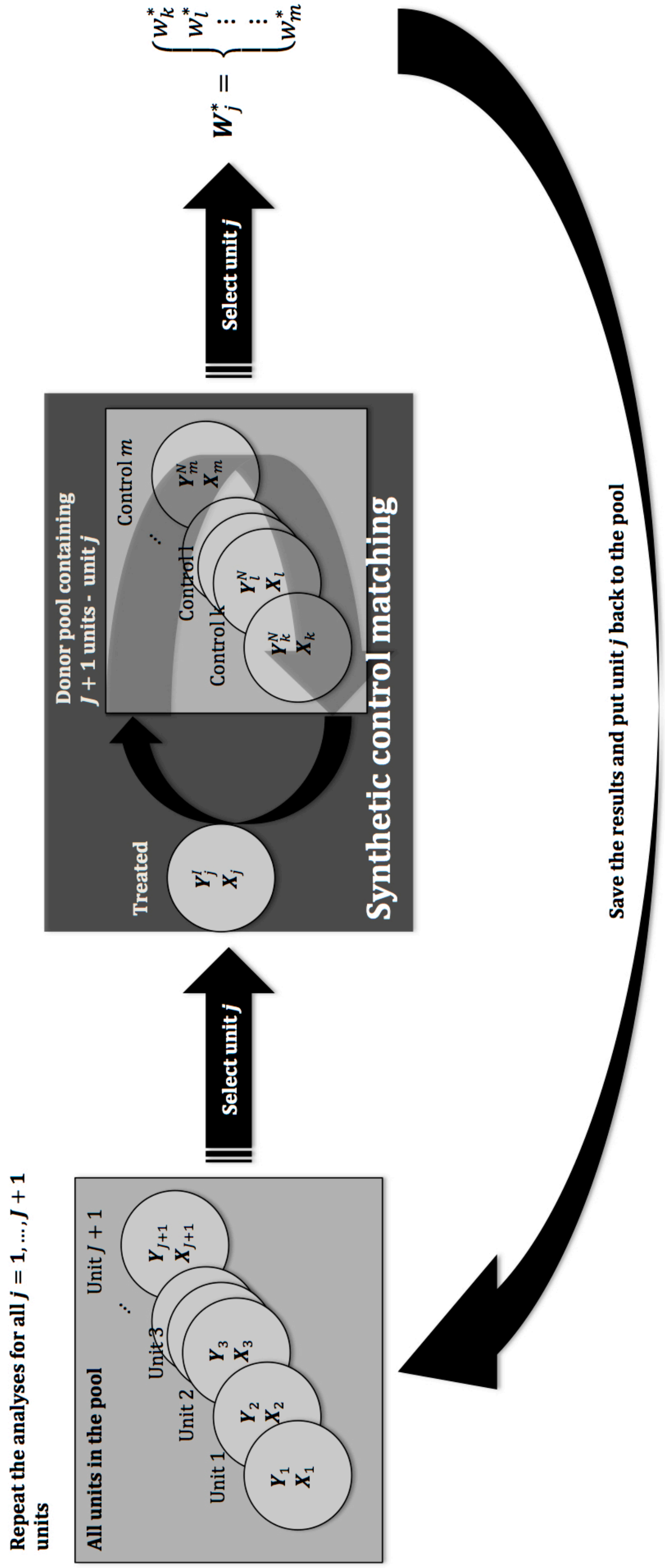
The third and very powerful test was proposed by Abadie et al. (2010) and is so-called "in-space placebo". The idea of this test is related to the permutation inference (see Rosenbaum (1995, 2002)), where the distribution of a test is computed under random permutation of the sample units' assignments to the treatment and control groups. Contrary to the single-unit placebo we apply the synthetic control method to every potential control in the sample, and we include the treated unit in the donor pool too.

In practice, we iteratively apply the synthetic control method used to estimate the treatment effect to every control unit in the donor pool. The placebo permutation procedure is described by the figure 2.6. In each iteration, we reassign the treatment to one of the control units shifting treated unit to the donor pool. That is, we proceed as if one of the controls in the donor pool would have received a treatment in time $T_0 + 1$, instead of the treated unit. Each iteration would produce the set of weights for the respective synthetic control. We then compute the estimated effect associated with each placebo run. This iterative procedure provides us with a distribution of estimated gaps for the units where no treatment tooks place. This allows to assess whether the effect estimated by the synthetic control for the treated unit is large relative to the effect estimated for a randomly chosen control units.

Note that, regardless of a number of available control units, time periods, and use of individual or aggregated data it is always possible to calculate the empirical distribution of the estimated effect of the placebo treatment. The test gives us an informative inference under the following recommendation:

Recommendation 3.

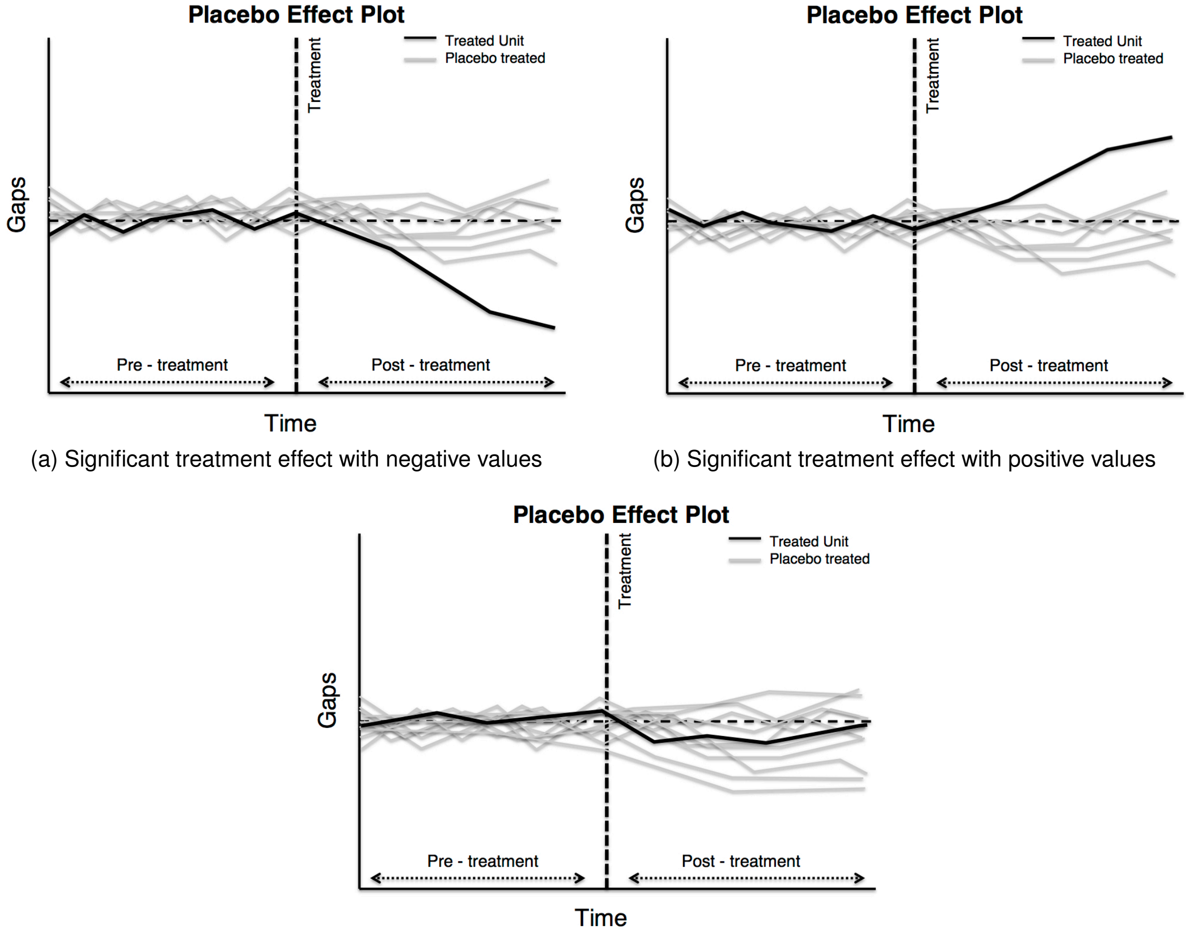
The recommendation for the in-space placebo test is based on hypothesis of no treatment, that is, the estimated effect of the treatment is not expected to be abnormal relative to the distribution of the placebo effects, and vice versa.



Source: Author's elaboration.

Figure 2.6: In-space placebo procedure

Few examples of the “placebo effect graphs” that report the values of treatment effect for the treated unit (black line) and the “placebo-treated” units (grey line) are presented in the figure 2.7.



(a) Significant treatment effect with negative values

(b) Significant treatment effect with positive values

(c) No-significant treatment effect

Source: Author’s elaboration.

Figure 2.7: Different examples of placebo effect plots

Significant evidence and interpretation

If the placebo studies show that the gap estimated for the treated unit is large relative to the gaps for most of the control units that did not participate in the treatment program, then the interpretation is that the analysis provides significant evidence of a treatment effect on the treated unit. The figures 2.7a and 2.7b show the treated units with significant treatment effect. Note that in these two cases we imperatively suppose that the treatment effect on the first graph should be of relatively large negative value and relatively large positive value for the second placebo effect graph. If this is not the case, then both figures might show no-significant treatment effect as all placebo-treated units would show larger treatment effect compare to the treated unit itself.

If, on the other hand, the placebo studies create gaps of the magnitude similar to the one estimated for the treated unit, then the interpretation is that the analysis does not provide significant evidence of a treatment effect for a treated unit. This case is represented by figure 2.7c, where the treated unit, even though it does show treatment effect with negative values, lays in the middle of the placebo-treated units, and so other "placebo-treated" units have created larger treatment effect and our estimation for the treated unit is not validated.

Moreover, the placebo effect graphs provide us a tool to calculate a specific p-value, described in the following definition:

Definition 2.1 (Pseudo p-value)**.**

The pseudo p-value assesses the estimation of the treatment effect by comparing the distribution of placebo effects and the estimated treated unit effect. We assume for each placebo unit one of the two possibilities: "bad estimation", which gives similar or larger treatment effect for the control than the treated unit, or "good estimation", which means missing or small treatment effect for the control. The p-value is constructed as the fraction of a number of bad estimations over a total number of units used in a test sample, given by following formula:

$$\text{Pseudo p-value} = \frac{\text{Number of bad estimations}}{\text{Number of test units}}. \tag{2.12}$$

We interpret the p-value as the probability of obtaining an estimate at least as large as the one obtained by the unit of interest when the treatment is reassigned at random in the data set.

If the value of the pseudo p-value is close to zero, there is a small chance to get such a good estimate as the one obtained by the treated unit, and so we can validate the significant effect of the treatment on the unit of interest. On the other side, if the pseudo p-value is large, the validation of the significant treatment effect is quite difficult.

2.3.2 Root mean squared prediction error

Put aside the placebo tests, another important measure to evaluate the estimates is the root mean squared prediction error (RMSPE), that can be calculated for any unit and any time period. In this section, we present not only the RMSPE, but also the RMSPE-ratio and its p-value, starting with the root mean squared prediction error definition:

Definition 2.2 (Root mean squared prediction error)**.**

"RMSPE calculates the lack of fit between the path of the outcome variable for any particular unit and its synthetic counterpart" (Abadie et al. (2015, p. 502)). A general RMSPE for unit k calculated between two periods t_1 to t_2 is defined as:

$$\text{RMSPE}_{(k,t_1,t_2)} = \left(\frac{1}{n_t} \sum_{t=t_1}^{t_2} \left(Y_{kt} - \sum_{l \in \mathbb{J} \setminus k} w_l^* Y_{lt} \right)^2 \right)^{1/2}, \tag{2.13}$$

where n_t is the number of periods for which we calculate the RMSPE, $(t_1,t_2) \in \{1,\ldots,T\}$, $k \neq l$ and $(k,l) \in \mathbb{J} = \{1,\ldots,J+1\}$.

Most often, we first calculate the RMSPE for pre-treatment and post-treatment periods of the treated unit under investigation. That is, the pre-treatment RMSPE for unit $k = 1$ between $t_1 = 1$, $t_2 = T_0$, and post-treatment RMSPE for the same unit between periods $t_1 = T_0 + 1$, $t_2 = T$. With these two measurements we compute the RMSPE-ratio:

Definition 2.3 (Root mean squared prediction error ratio)**.**

RMSPE-ratio calculate the ratio between pre-treatment RMSPE and post-treatment RMSPE, that is:

$$\text{RMSPE-ratio} = \frac{\text{Post-treatment RMSPE}}{\text{Pre-treatment RMSPE}}. \tag{2.14}$$

After running a placebo tests, it is common to calculate the RMSPE and RMSPE-ratio for each unit in the testing sample, whether it concerns only one unit after the single-unit and in-time placebo tests, or all units from the donor pool after the in-space placebo test. Note that in order to calculate the RMSPE for the placebo-treated (meaning the control unit), we use the respective placebo synthetic control that was generated during the placebo test. In a case of in-space placebo or also in-time placebo for multiple time periods, we can calculate the RMSPE-ratio p-value, which has the following definition:

Definition 2.4 (Root mean squared prediction error p-value)**.**

RMSPE-ratio p-value gives us the proportion of units with higher RMSPE-ratio than the treated unit, that we so-called “bad RMSPE-ratio estimation”, to total number of tested units, that is:

$$\text{RMSPE-ratio p-value} = \frac{\text{Number of RMSPE-ratio bad estimations}}{\text{Number of tested units}}. \tag{2.15}$$

If the RMSPE-ratio for the treated unit is relatively large compare to the rest of the controls in the donor pool, it implies that no control unit achieves such a large ratio. We can interpret it as: *“if one were to assign the treatment at random in the data, the probabilities of obtaining a RMSPE-ratio as large as the treated unit one is $1/(J+1)$”* (Abadie et al. (2010, p. 503)).

Note that we have to be careful when interpreting the resulting p-value, as we do not always have a sufficient number of units in the donor pool to validate the significance of the treatment effect. That is why, it is important to take into account all other measures as the graph analysis, placebo tests and RMSPE itself.

Interpretation of RMSPE indicators

Table 2.7 gives us an overview, how to interpret the results of RMSPE indicators in case of relatively large or relatively small values. Note that the RMSPE is a scale-less measure, though the term “relative” is with respect to the values of the potential outcome, treatment effect and the rest of the units in the donor pool. Note also that the RMSPE is not a measurement of a significance of the treatment effect, but helps in its interpretation and justification.

	Relatively large	Relatively small
Pre-treatment RMSPE	Might indicate that the synthetic control does not provide a good match to the treated unit. Very large value eventually indicates a problem of extreme value observation. In other words, there is no combination of units in the sample that can reproduce the time series of the potential outcome prior to the treatment;	Is a first sign of the good match between the treated and its synthetic control. Should be the case for majority of the control units in the donor pool in order to indicate that the synthetic control method is able to provide a good fit for potential outcome path prior to the treatment;
Post-treatment RMSPE	Shows potentially large treatment effect, but is not indicative of large effect of the intervention if the pre-treatment RMSPE is also large;	Is not indicative of a large treatment effect;
RMSPE-ratio	Indicates large treatment effect for a given unit;	Indicates that there is not a significant improvement with respect to the pre-treatment period;
RMSPE-ratio p-value	Does not approve large significant treatment effect.	Approve the significant treatment effect. Remark: we have to check the pseudo p-value as well.

Source: Author's elaboration.

Table 2.7: Interpretation of root mean squared prediction error measures

Excluding observations with respect to RMSPE from the placebo test donor pool

There is one important remark with respect to the placebo test and the RMSPE. Note that RMSPE-ratio does not imply the cutoff for the exclusion of miss-fitting placebo runs. That is, if the synthetic control had failed to fit the outcome path in pre-treatment period, then much of the post gap between the treated and its control was also artificially created by the lack of fit rather than by the treatment effect. Similarly, placebo runs with poor fit prior to the treatment do not provide information to measure the relative rarity of estimating a large post-treatment gap for a unit that was well fitted prior the treatment.

Note that for inference placebo analysis Abadie et al. (2015) suggest to exclude units beyond a certain level of pre-treatment RMSPE. They recommend to use the units from the donor pool with RMSPE that are smaller than two to five times RMSPE of the unit of interest. This will provide the focus exclusively on those units that can fit almost as well as the treated unit in the pre-treatment period. Nevertheless, the choice of the threshold should stay arbitrary and unique to each study, as it is dependent on the relative size of the RMSPE.

2.3.3 Robustness tests and other analysis

The placebo tests and the RMSPE indicators are mostly measuring the good fit of the matching and the significance of the results of the analysis. It could be that we are also interested in other measures of the modelling.

In this section, we briefly present two robustness checks of the model: sensitivity analysis of a number of controls and sensitivity analysis of a number of variables. Moreover, we also present two other analyses related to the treatment effect: predictor analyses and evolution test.

Sensitivity analysis of number of controls: "leave one out"

In some cases, while using the synthetic control, we may consider only a small number of controls in the donor pool in order to closely examine each control's characteristics and outcome. Reducing the number of units in the synthetic control group may impact the extent to which the synthetic control units is able to fit the characteristics of the unit of interest. In this case, one has to examine a trade-off between sparsity and goodness of fit in the choice of the number of units that contribute to the synthetic control. In order to test the sensitivity of the results to the changes in the units weights, $\mathbf{W}^*$, we can run the robustness tests proposed by Abadie et al. (2015). By the specific robustness checks we analyse the sparsity of the synthetic controls, that is, synthetic controls that involve a small number of comparison units.

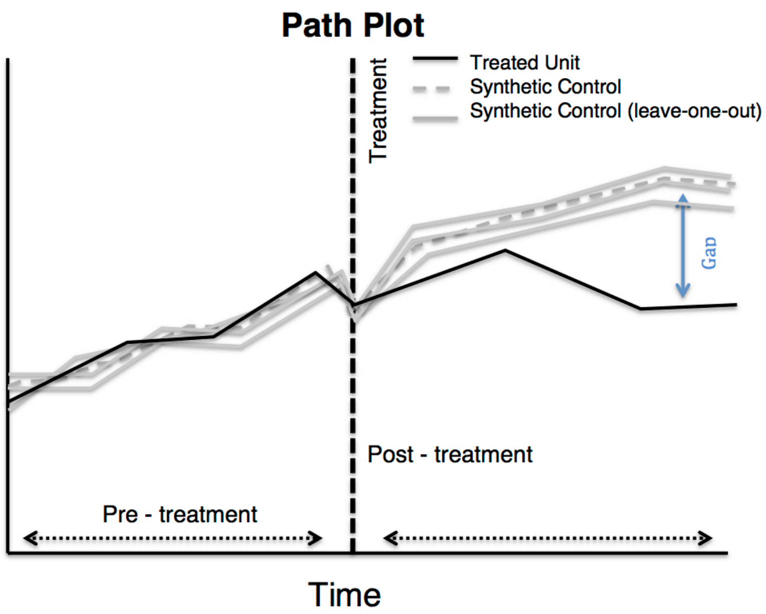
The point is to iteratively reestimate the baseline model to construct a synthetic control omitting in each iteration one of the units that received a positive weight in the synthetic control. At each iteration we take one unit out, going from the unit that has the less weight (effect) in the synthetic control to the one that has the most influence in the synthetic control. By excluding units that received a positive weight we sacrifice some goodness of fit, but this sensitivity check allows us to evaluate to what extend our result are driven by any particular control unit.

First, we can visualise the results on the leave-one-out distribution graph. An example of such a graph is presented on the figure 2.8, which is the path plot with three other synthetic controls constructed with less of the controls in the respective donor pool.

In order to verify the robustness, we want the leave-one-out synthetic controls to be as similar as possible to the primary synthetic control. In a case of large deviation form the original synthetic control, the model needs a closer verification.

Another way to check the robustness of the results is to build the tables containing the predictors (see table 2.6) for the treated unit, the synthetic control and all leave-one-out synthetic controls. We can build as many tables as the number of units in the donor pool.

Abadie et al. (2015) show the potential gain from using combinations of units rather than single countries as comparison cases in comparative research. Abadie et al. (2015) also show that usually, the synthetic control is robust to the inclusion of discarded units, if the units did not have much impact in the synthetic control.



Source: Author's elaboration.

Figure 2.8: Leave-one-out distribution of the synthetic control for the treated unit

Sensitivity analysis of number of variables

Another way to check the robustness of the model is to include additional predictors of the outcome variable used to construct the synthetic control. As for the leave-one-out robustness test, we can also construct different path plot graphs or tables. But this kind of analysis might be very time and resources demanding. Though, we would suggest analysing the (v) loss function, that is, the loss associated with equation 2.9.

A good model should stay unaffected regardless of which and how many predictor variables we include. And an optimal model will have a small (v) loss function, and so by including other predictors, the value of the (v) loss function should stay relatively unaffected. If it is not the case, we might have to consider including the new predictors into the model in order to increase the quality of the estimation.

Moreover, note that by including confounding variables C into the model, we are naturally increasing the (w) loss function (the loss associated with equation 2.8), but at the same time generally increasing the quality of the estimation.

Evolution test

The last test presented in this section analyses whether the treatment explains the gap of the outcome variable between the treated and the synthetic control. To do so, we can check the evolution of the gap and another indicator of the intensity of the treatment. Both of the variables are placed on the same graph. Abadie and Gardeazabal (2003), for example, check the number of deaths as an indicator of the terrorist activity (treatment) and the per capita GDP gap (treatment effect)

On the one hand, this test is good in case we have evolution in the intensity of the treatment. On the other hand, we cannot apply the test if we do not have an intensity indicator. In order to test the evolution, we can, for example, use an impulse-response function or polynomial distributed lag models (see Abadie and Gardeazabal (2003) for more details).

Another possibility to use the evolution test is when we need a closer examination of the predictors. It could be that the gap is explained by another factor than the treatment, and this factor itself can be explained by one of the predictors. In case we detect a potential "effect" disturbance, that is the sudden unexpected increase or decrease in the treatment effect, we analyse a predictor that has an important value in the synthetic control (high value of v^* in the predictor matrix $\mathbf{V}^*$).

We check graphically any gaps of different predictors between the treated unit and its synthetic control. If we observe the relatively substantial gap between the two paths, then this predictor may contribute to the explanation of the treatment effect and need closer analysis.

Chapter 3

Environmental problematics at the international and firm's level, and Carbon Disclosure Project

The average temperature has already risen by approximately 0.85℃ since 1880.[1] This change is proved to be mostly due to the human activity.[2] Besides households, the major contribution to the climate change is caused by the companies and their non-environmental behaviours. As a result, there is increasing pressure on the firms and institutions to review their politics.

Since half a century, many countries and regions are taking action to prevent the irreversible phenomena of the global warming. As an example, we can mention the European Union, California and China that are among those with the most ambitious policies that will reduce Greenhouse Gas (GHG)[3] emissions. In addition, a basis for international co-operation is provided by, for example, the United Nations Framework Convention on Climate Change, the Kyoto Protocole, and the Paris Agreement, along with a range of partnerships and other approaches.[4]

In this chapter, we first briefly explain the reason why it is so important to reduce the carbon emissions. And then we introduce different international organisations and regulations related to the climate change. This first section contains some information about the United Nations Environment Programme, the United Nations Framework Convention on Climate Change, or the Intergovernmental Panel on Climate Change.

[1] Source: IPCC 2013: Climate Change 2013: The Physical Science (Working Group I to the Fifth Assessment Report (2013)).
[2] Source: IPCC 2014: Climate Change 2014: Synthesis Report (Core Writing Team et al. (2015)).
[3] Greenhouse gas: A gas that contributes to the greenhouse effect by absorbing infrared radiation. Carbon dioxide and chlorofluorocarbons are examples of greenhouse gases [Oxford Dictionaries].
[4] Source: The Economic of Climate Change: The Stern Review (Stern (2006)).

The second section introduces the problematic of the climate change on the firm's level. It overviews the main disclosing programs. With exception of the Carbon Disclosure Project (CDP), the following programs are presented: the Global Reporting Initiative, the United Nation Global Compact, the International Organisation for Standardisation 14000, or the Greenhouse Gas Protocol. The second part of this section reviews some initiatives and regulations promoting a low-carbon economy and aiming the reduction of industrial GHG emissions in the European Union, the United Kingdom and the United States. The reason for selecting these three geographic regions is that we use them in our empirical analysis.

Finally, the last section of this chapter presents the Carbon Disclosure Program, one of the binding reporting standards that are evaluated by our study presented in chapter 5. We first present the main collaborations between CDP with investors, governments and other international organisations. And then we briefly introduce the main programs that are proposed to the firms and cities.

3.1 Climate change, international organisations and different regulations

Last Intergovernmental Panel on Climate Change assessment reports, the Fifth Assessment Report released between 2014 and 2015, confirms clear and growing human influence on the climate system, with impacts observed across all continents and oceans. This climate change is due to the increasing GHG concentration in the atmosphere, chemical pollution, abuse of the land use, deforestation, bad water or waste management and many other factors. In this work, we are not part of the sceptical environmentalists, and we do strongly believe that the climate change is due to the human activity with its fatal impact on the entire ecosystem.

The Climate Change 2014 Synthesis Report (Core Writing Team et al. (2015, p. 4)) confirms that: *"Anthropogenic greenhouse gas emissions have increased since the pre-industrial era, driven largely by economic and population growth, and are now higher than ever. This has led to atmospheric concentrations of carbon dioxide, methane and nitrous oxide that are unprecedented in at least the last 800000 years."*

The Stern Review (Stern (2006, p. 3)) asserts that: *"If annual greenhouse gas emissions remained at the current level, concentrations would be more that treble pre-industrial levels by 2100, committing the world to 3-10℃."* This increasing GHG concentration has as consequences, inter alia, dramatical raise of temperature, and at its turn the warming of oceans, melting ices, increase of the see level and delocalisation of water system.

These alarming facts urged the governments, institutions, authorities and investors to take the responsibilities in order to promote more sustainable and less polluting systems or economies. As an answer, in the early 70's, the pro-environmental international organisations and agreements saw their light. There was a universal initiative to build a framework related to climate change, promoting the reduction of CO_2[5] emissions, as for example the emissions trading, technology cooperation, or actions to reduce deforestation and waste.

In this section, we give a small snapshot of few international organisations, regulations and existing agreements. Note that this is not an exhaustive list but only an overview of the core structure.

3.1.1 International organisations and regulations

As already mentioned, it is since early 70's that there is a development of environmental organisations and tendencies to regulate the climate change. Nowadays, we can account for an endless list of environmental organisations and agreements, divided by the status of intergovernmental, governmental or non-governmental institutions, and subdivided in continental, international, regional or local organisations. In this section, we present few of the international intergovernmental organisations, namely, the United Nations Environment Programme, the United Nations Framework Convention on Climate Change, its related Kyoto Protocol and Paris Agreement, and finally, we shortly describe the Intergovernmental Panel on Climate Change.

United Nations Environment Programme

United Nations Environment Programme (UNEP) was founded in Nairobi (Kenya) in 1972. UNEP is one of the first and the leading global environmental authority. It sets the global environmental agenda, promotes the coherent implementation of the environmental dimension of sustainable development within the United Nations system and serves as an authoritative advocate for the global environment.

The UNEP mission is: *"To provide leadership and encourage partnership in caring for the environment by inspiring, informing, and enabling nations and peoples to improve their quality of life without compromising that of future generations.*[6]*"* Their focus is, for example, on the climate change, disasters, ecosystem management, environmental governance, waste and resource efficiency. They get their work enclosed by: Assessing global, regional and national environmental conditions and trends; developing international and national environmental instruments; and strengthening institutions for the wise management of the environment.

As already mentioned, UNEP stays in a position of one of the most important environmental organisation. It has played a significant role in developing environmental conventions, promoting environmental science and information. The organisation helps with development and implementation of policy with national governments, regional institutions in conjunction with environmental non-governmental organisations.

[5] Carbon dioxide, even though naturally present in the atmosphere is the primary greenhouse gas emitted through human activities. Based on global emissions from 2010, the CO_2 accounts for 65% of the global greenhouse gas emissions (Source: IPCC 2014: Climate Change 2014: Synthesis Report (Core Writing Team et al. (2015))). That is why, we often take the carbon dioxide as a proxy of the greenhouse gas.

[6] Source: United Nations Environment Programme. Retrieved July 20, 2016, from http://www.unep.org/about/.

United Nations Framework Convention on Climate Change

The United Nations Framework Convention on Climate Change (UNFCCC) is an international environmental treaty negotiated at the Earth Summit in Rio de Janeiro in 1992 and entered into force in 1994. In 2015, the Convention included 197 ratifying countries that are so-called Parties to the Convention. Its ultimate objective is to achieve *"... stabilisation of greenhouse gas concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system.[7]"*

Since 1995, the Parties to the convention have annual meetings so-called Conferences of the Parties. Two important universal agreements were established on these conferences, respectively the Kyoto Protocole in 1997 and the Paris Agreement in 2015. These two agreements are briefly described in the following paragraphs.

Kyoto Protocol

The Kyoto Protocol is an international agreement linked to the UNFCCC, that aims to reduce carbon dioxide emissions and the presence of greenhouse gases. The Kyoto Protocol was adopted in Kyoto (Japan) in 1997, and due to a complex ratification process, it entered into force in 2005 only.

Mainly, the Kyoto Protocol commits its Parties by setting internationally binding emission reduction targets. The Kyoto mechanisms that help to stimulate green investment and help Parties to meet their emission targets in a cost-effective way are: International Emissions Trading, Clean Development Mechanism and Joint Implementation.

With respect to the UNFCCC the Convention says: *"In short, the Kyoto Protocol is what "operationalises" the Convention. It commits industrialised countries to stabilise greenhouse gas emissions based on the principles of the Convention. The Convention itself only encourages countries to do so.[8]"*

The Paris Agreement

At the 21st Paris climate conference in December 2015, 195 countries adopted the first-ever universal, legally binding global climate deal, that was called "Paris Agreement". The agreement sets out a global action plan to put the world on track to avoid dangerous climate change by limiting global warming to well below 2℃. The agreement is due to enter into force in 2020.

[7] Source: Introduction to the Convention. Retrieved July 19, 2016, from http://unfccc.int/essential_background/convention/items/6036.php.

[8] Source: Kyoto Protocol Intro. Retrieved July 26, 2016, from http://unfccc.int/essential_background/kyoto_protocol/items/6034.php.

Intergovernmental Panel on Climate Change

Intergovernmental Panel on Climate Change (IPCC) is the international intergovernmental organisation evaluating the science related to climate change. The IPCC was set up in 1988 by the World Meteorological Organisation and UNEP. Currently IPCC counts for 195 countries as members of the organisation.

This body provides policymakers with regular assessments of the scientific basis of climate change, its impacts and future risks, and options for adaptation and mitigation. IPCC assessments issues a scientific basis for governments at all levels to develop climate-related policies, and they underlined negotiations at the United Nations (UN) Climate Conference – the UNFCCC.

IPCC counts for several working groups and the task forces to provide different reports on the regular basis. Among, we should mention the assessment reports, social reports, methodology reports or new scenarios. These accounts are the daily basis for further scientific work or serve as a support in governments decisions.

3.2 Climate change regulation at the firm's level

As already explained in the previous part of this chapter, the world is more aware of climate change and so increasingly sensitive to the "green" economics in order to assure the future. Consequently, companies, the major GHG emitters, are pushed too rapidly and significantly cut down their CO2 emissions and review their policies in this direction. On one side, this problem is regulated by the governments and authorities and, on the other side, there is also rising pressure from the investors and stakeholders. Therefore, the companies have to react accordingly.

The sustainable behaviour of firms received closer attention only in the last three decades, and since then the companies started slowly report their CO2 emissions. Mostly, the companies first published their environmental activities in the annual reports. Later, they started to disclose their social and environmental responsibility and sustainability reporting into so-called Corporate Social & Sustainability Report (CSR).

In the beginning, the reported values were highly inaccurate, and the firms needed a better guidance in how to collect and disclose the data. The companies did not have to wait long for this help, and many governments, private companies or non-governmental organisations are now proposing a multitude of programs to this effect. As an example, we can mention the United Nation Global Compact, Global Reporting Initiative, the Greenhouse Gas Protocol, or the Carbon Disclosure Project. The main objectives of these organisations are to help the companies with the environmental management, as well as to build the CSR of good quality. The first three programs are briefly described in next sub-sections. The Carbon Disclosure Project gets some more attention in the section 3.3, as it is the program that is studied in our empirical part.

Moreover, apart from the few disclosing programs, we shortly review the most common regulations in the European Union, the United Kingdom and the United States. As already mentioned, the choice of these regions is related to the study in chapter 4. The main regulations on the firm level in these regions are the UK Carbon Reduction Commitment Energy Efficiency Scheme and the US Environmental Protection Agency's Mandatory GHG Reporting Rule. Note that the UK is not purposely included in the EU, because of its specificity in sustainable development strategy.

3.2.1 Overview of the main disclosing programs

This section briefly reviews the main disclosing programs existing to serve the corporations, governments, investors and stakeholders.

Global Reporting Initiative

The Global Reporting Initiative (GRI), founded in 1997 in Boston (US), is an international independent standards organisation. It has as an objective to help businesses, governments and other institutions to understand and communicate their impacts on issues such as climate change, human rights, corruption and many others.

The GRI is a nonprofit organisation and has strategic partnerships with a range of international institutions, such as the International Organisation for Standardisation, the United Nations Environment Programme, the United Nations Global Compact, the International Integrated Reporting Council, and the Carbon Disclosure Project, among others.

The GRI is a pioneer in sustainability reporting. Thousands of reports are coming yearly from over 90 countries. The GRI provides the world's most widely used standards on sustainability reporting and disclosure. This information enables businesses, governments and citizens to make better decisions based on information that matters. The GRI's sustainability reporting standards are used in 35 countries in their sustainability policies and look to them for guidance.

GRI possesses so-called Sustainability Disclosure Database, which is one of the biggest database containing the disclosing reports, including over 9300 organisations, 34000 reports and 23790 GRI reports. Note that the database contains three different kinds of reports: GRI reports[9], GRI-Referenced Reports[10], Non-GRI reports[11].

In 2013, the GRI introduced the GRI Content Index that is a sustainability reporting template that offers a quick overview of an organisation's publicly accessible information on economic, environmental, social and governance performance.

[9] GRI reports use the GRI Sustainability Reporting Framework and have a GRI Content Index.

[10] GRI-Referenced Reports make reference to or use elements of GRI's Sustainability Reporting Framework but do not include a GRI Content Index.

[11] Non-GRI reports are any other type of sustainability, corporate responsibility, or integrated report which does not reference or use the Guidelines.

United Nation Global Compact

The United Nation Global Compact (UNGC) is a United Nations initiative, founded in 2000, to encourage businesses worldwide to adopt sustainable and socially responsible policies and to report on their implementation.

United Nation Global Compact is calling itself as the "The world's largest corporate sustainability initiative". Its mission is: *"A call to companies to align strategies and operations with universal principles on human rights, labour, environment and anti-corruption, and take actions that advance societal goals.*[12]*"* In a way this is very similar to what the Global Reporting Initiative promotes.

Today, UNGC involves 12000 signatories in 170 countries, both developed and developing, representing nearly every sector and size. Moreover, it promotes the sustainability reporting as a mainstream for both companies and non-business organisations. This annual report, called Communication on Progress (COP), is a requirement to be a part of the UN Global Compact, and provides valuable information to the stakeholders. In 2014, 5404 COP were submitted, and based on a company's self-assessment, each COP falls into one of the following differentiation levels: Global Compact (GC) Advanced[13], GC Active[14], GC Learner[15].

International Organisation for Standardisation 14000

International Organization for Standardisation (ISO) 14000 is a series of standards developed by the International Organisation for Standardisation related to the organisational environmental management. The ISO 14000 standards is an existing framework that helps organisations to systematise and improve their environmental management efforts. Note that the ISO 14000 standards are not designed to assist the enforcement of environmental laws, or to regulate the environmental behaviour of organisations and its adherence is non-compulsory.

The ISO 14001 standard is the most important standard within the ISO 14000 series. ISO 14001 is based on the Plan-Check-Do-Review-Improve cycle and specifies the requirements of an environmental management system, that is, a systemic approach to deal with environmental management for organisations.

Even though there is not an official requirement for companies and institutions to wear the label ISO 14001, to do so gives them the marker "green". This impulse satisfies the investors, stakeholders, consumers and after all the whole organisation can take advantage of basic environmental management tools.

[12] Source: What is the UN Global Compact | UN Global Compact. Retrieved July 28, 2016, from http://www.unglobalcompact.org/what-is-gc.

[13] GC Advanced is a COP that qualifies as GC Active and, in addition, covers the company's implementation of advanced criteria and best practices.

[14] GC Active is a COP that meets the minimum requirements.

[15] GC Learner is a COP that does not meet one or more of the minimum requirements.

Greenhouse Gas Protocol

The Greenhouse Gas Protocol (GGP) Initiative is a multi-stakeholder partnership of businesses, non-governmental organisations, governments, and others. The Initiative was launched in 1998 by the World Resources Institute and World Business Council on Sustainable Development. GGP is convened by the two organisations, plus a US-based environmental non-governmental organisation and a Geneva-based coalition of 170 international companies. Its mission is to set the global standard for how to measure, manage, and report greenhouse gas emissions.

The GGP Initiative comprises two separate but linked standards: GHG Protocol Corporate Accounting and Reporting Standard (this document provides a guide how to quantify and report the GHG emissions); and GHG Protocol Project Quantification Standard (a guide for quantifying reductions from GHG mitigation projects).

The first edition of the Greenhouse Gas Protocol, A Corporate Accounting and Reporting Standard, was published in 2001 and since hundreds of companies and organisations around the world are using GGP standards and tools to manage their emissions and become more efficient, resilient, and prosperous organisations.

GGP offers not only the corporate protocols and standards, but also guidances, calculation tools to assess the emissions or life cycles, and online training. Moreover, in 2006, the International Organisation for Standardisation adopted the Corporate Standard as the basis for its ISO 14064-I.

To amplify the importance of this standard, the Greenhouse Gas Protocol states: *"The 2010 GHG Workforce Survey from GHG Management Institute and Sequence Staffing found that the overwhelming majority of respondents said GHG Protocol is the second most important climate program after Kyoto Protocol in the successful measurement and management of climate change.*[16]*"*

3.2.2 Overview of the European, British and American low-carbon politics

In this section, we briefly introduce the European Union, the United Kingdom and the United States climate regulations. For example, we overview the regulations and organisations as the Emission Trading System, United Kingdom Climate Change Programme, the Carbon Reduction Commitment Energy Efficiency Scheme, or the US Environmental Protection Agency.

[16]Source: About the GHG Protocol. Retrieved July 25, 2016, from http://www.ghgprotocol.org/about-ghgp.

Overview of the European Union climate regulations

As already mentioned, the European Union is one of the leaders in climate change prevention. The European Commission proposes diverse climate strategies and has set itself targets for reducing its greenhouse gas emissions progressively up to 2050. These targets are defined to achieve the transformation towards the low-carbon economy. The EU tracks its progress on cutting the GHG emissions through monitoring and reporting. Each new policy is first carefully assessed by the European Commission of its potential impacts. The main EU climate change prevention strategies are the Emission Trading System or the Effort Sharing Decision, described in following paragraphs.

Emission Trading System

The EU Emission Trading System (ETS) is a main EU policy to confront climate change and its key tool for reducing industrial GHG emissions. It is the world's first major carbon market and still today remains the biggest one. The EU ETS operates in 31 countries (all 28 EU countries plus Iceland, Liechtenstein and Norway), limits emissions from more than 11000 heavy polluting installations and airlines, and covers around 45% of EU's greenhouse gas emissions.

The EU ETS is based on the "cap and trade system". That is, there is a certain amount of greenhouse gases that can be emitted by the installations covered by the system, and the companies receive or buy emissions allowances which they trade with one another as needed. Note, that the amount of trading permits is reduced over time, in order to assure the long-term decrease in the emissions.

Other EU climate strategies

Another climate action is the so-called Effort Sharing Decision that establishes binding annual greenhouse gas emission targets for the Member States for the period 2013–2020. These targets concern emissions from most sectors not included in the EU ETS, such as transport, buildings, and agriculture. The target, although very similar to the one for the EU ETS, is to form a set of policies that will help move towards a low-carbon economy.

Aside from the previous strategies, EU also focus on low carbon technologies, improvement of transport, protection of the ozone layer, forest and agriculture. Furthermore, it takes international actions on climate change such as being part of the UNFCCC, bilateral relations with non-EU countries, policies and initiatives at EU and international level, and financing to support developing countries in their efforts to tackle climate change.

What is more, the EU also proposes the European Climate Change Programme containing a comprehensive package of policy measures to reduce greenhouse gas emissions. This program is applied on the European level, but also encourages each of the EU Member States to put in place the domestic actions that are built on the specific European Climate Change Programme measures or complement them.

Overview of the United Kingdom climate regulations

The United Kingdom climate change protection is one of the strongest in the world. The government puts a lot of pressure on the private as well as public sector to cut down their CO_2 emissions, review and implement new environmental strategies, obliges them to report their sustainable data and pushes them to participate in many of the environmental programs. In this section, we present few main organs and strategies implemented in the United Kingdom to regulate the low-carbon economies.

Department of Energy & Climate Change

Apart from being a member of the European Union Emissions Trading System, the UK government has its own Department of Energy & Climate Change. It makes sure that the UK has secure, clean, affordable energy supplies and promote international action to mitigate climate change. One important role of the department is, setting the carbon budget that places a restriction on the total amount of greenhouse gases the UK can emit over a 5-years period.

United Kingdom Climate Change Programme

The United Kingdom signed the Framework Convention on Climate Change in 1992 and has been signed up to the Kyoto Protocol since 1995. In January 1994 it published its first UK Programme on Climate Change, identifying its obligations and commitments to help tackle the problem of global warming.

In 2000, the UK Government undertook a major reappraisal of the Climate Change Programme, and in order to implement the strategy, in 2008 the government introduced the Climate Change Act. This Act established a framework to develop an economically credible emissions reduction path. The UK government states: *"The Climate Change Act also strengthened the UK's leadership internationally by highlighting the role it would take in contributing to urgent collective action to tackle climate change under the Kyoto Protocol.[17]"*

Carbon Reduction Commitment Energy Efficiency Scheme

In 2007, UK introduced a program called Carbon Reduction Commitment Energy Efficiency Scheme that intends to promote and reduce the GHG emissions. It is a mandatory carbon emissions reduction scheme in the United Kingdom that applies to large non-energy-intensive organisations in the public and private sectors. It has been estimated that the scheme will reduce carbon emissions by 1.2 million tonnes of carbon per year by 2020. Concerning the operating mechanism, the Carbon Reduction Commitment Energy Efficiency Scheme involves self-certification of emissions and is managed by Environment Agency[18].

[17]Source: The Climate Change Act and UK regulations. Retrieved July 28, 2016, from https://www.theccc.org.uk/-tackling-climate-change/the-legal-landscape/global-action-on-climate-change/.

[18]Environment Agencies an executive non-departmental public body, sponsored by the Department for Environment, Food & Rural Affairs.

As a complement, there was the introduction of the Committee on Climate Change, an independent statutory body established under the Climate Change Act 2008. Its purpose is to advise the UK Government and Administrations on emissions targets and report to Parliament on progress made in reducing greenhouse gas emissions and preparing for climate change.

The committee provides independent advice to Government on setting and meeting carbon budgets and preparing for climate change. Above that, it monitors progress in reducing emissions and achieving carbon budgets. The committee also conducts an independent analysis into climate change science, economics and policy engagements with a wide range of organisations and individuals to share evidence and analysis.

Overview of the United States climate regulations

In 2011, the United States were placed as the second biggest world CO2 emitter, counting for about 16% of total emissions[19]. Even if they are a signatory part of the Kyoto Protocol since 1997, they have neither ratified nor withdrawn from the Protocol. Out of the three presented regions in this section, it is the one that puts the less effort to the climate change mitigation.

Nevertheless, there are established organisations and regulations to prevent the environment, as for example, the US Environmental Protection Agency or the Unites States Global Change Research Program, presented in the following paragraphs. Note, it was especially under the presidential of the Presidents G. W. Bush and B. Obama, that there was a strong requirement of national reduction of the greenhouse gas emissions.

United States Environmental Protection Agency

US Environmental Protection Agency is an agency of the US federal government founded in 1970 by the US President Richard Nixon. The Agency was created for the purpose of protecting human health and the environment by writing and enforcing regulations based on laws passed by Congress. The agency conducts the environmental assessment, research, and education.

In order to accomplish its mission, the Agency develops and enforces regulations based on Congress environmental laws. The Agency also enforces their regulations, and helps companies understand the requirements. They are in charge to help apply the environmental policy of the United States, which is a federal governmental action to regulate activities that have an environmental impact in the US.

Unites States Global Change Research Program

The United States Global Change Research Program was established by Presidential Initiative in 1989 and mandated by Congress in the Global Change Research Act of 1990 to: *"assist the Nation and the world to understand, assess, predict, and respond to human-induced and natural processes of global change.[20]"* The program coordinates and integrates global change research across 13 Federal agencies.

Their mission is to build a knowledge base through coordinated and integrated Federal programs of research, education, communication, and decision support. The focus is not only on the Nation but also on the cooperation with the rest of the world.

[19] Source: Carbon Dioxide Information Analysis Center. Retrieved July 24, 2016, from http://cdiac.ornl.gov/.

[20] Source: Legal Mandate of the US Global Change Research Program. About USGCRP. Retrieved August 04, 2016, from http://www.globalchange.gov/about.

3.3 Carbon Disclosure Project

Carbon Disclosure Project (CDP) is an independent international nonprofit organisation founded in 2003 and based in the United Kingdom. Its primary goal is to help the corporations and cities to disclose the greenhouse gas emissions and help them to manage the environmental risk. What distinguishes this organisation from any other disclosing projects is that the quality of the data reported to CDP is crucial and all data go under a loop of severe evaluations. The CDP collaborates with investors, companies, cities, governments and policymakers from all over the world.

Today, thousands of organisations from across all countries measure and disclose their environmental information through CDP. Thus it makes from CDP an organisation holding the largest collection of self-reported climate change, water and forest-risk data. The reported information is then put at the heart of financial and policy decision-making that motivates investors, corporations and governments to take action to prevent climate change and protect natural resources.

In this section, we first introduce the background of the Carbon Disclosure Project. That is we present the main purpose, numbers representing the CDP activities, and collaborations with investors, cities, governments, customers and other international organisations. In the second part of this section, we present the main programs proposed by CDP to the corporations. And we end up the section by giving some information about Carbon Disclosure Leadership Index and the Climate Disclosure Standards Board.

3.3.1 Introduction to the Carbon Disclosure Project

Carbon Disclosure Project is promoting collaboration and collective action that will achieve low-carbon economy. As they declare: *"We motivate companies and cities to disclose their environmental impacts, giving decision makers the data they need to change market behaviour.[21]"* Moreover, CDP tries to prevent dangerous climate change, protect natural resources, and improve the environmental management by using measurement and information disclosure.

As already mentioned, CDP is an international, nonprofit organisation that provides the only worldwide system for corporations and cities to measure, disclose and control their environmental information. The organisation has a multiple funding including philanthropic and government grants and donations, corporate and investor memberships, sponsorship and partnerships.

CDP has a global presence. It collects data from organisations and cities in some 60 countries, and its programs are used in 81 countries around the world. About 20% of global emissions are managed by the Program. More precisely, in 2003, CDP included only 253 reporting institutions, and this number increased to 5600 in 2015, including companies and cities. Moreover, CDP uses the Global partnerships to promote their mission. It possesses multitude local offices with local representatives that are responsible for implementing the disclosure process within their region.

[21] Source: CDP - Driving sustainable economies. Retrieved August 04, 2016, from https://www.cdp.net/en-US/Pages/-HomePage.aspx.

Apart of corporations, to whom CDP proposes multitude programs described in section 3.3.2, it also collaborates with the investors, cities, governments, policymakers, and forms different alliances with other pro-environmental organisations. Today, CDP works with 827 institutional investors, governments and policymakers holding US$100 trillion in assets. By providing a quality environmental data, the CDP helps the investors to drive investment flows towards a low carbon and more sustainable economy. Moreover, CDP manages about 2 billion metric tonnes of carbon emissions in 600 cities over the world. In the following text, we explain the relations that CDP had with investors, cities, customers, governments and other international institutions.

CDP investor initiatives

CDP works with investors in order to protect the long terms investments and provides them with data that support long-term objectives and analyses. That is, by providing the evidence about private sector greenhouse gas emissions, water usage, pro-environmental strategies, water and deforestation risks, CDP helps investors to build balanced portfolio reducing the long-term risks arising from environmental externalities.

Each investor has a possibility to become a signatory or member of the CDP, where the membership is an extension of the signatory. Being a signatory provides access to all company responses to the questionnaires which the investor endorses. The annual fee, although voluntary, was in 2016 US$975, but will become mandatory from 2017. The membership fee in 2016 was between US$7000 to US$9000, giving the access to all CDP responses, and gives access to software allowing easy analysis of company responses. Besides, the signatory investors have the possibility to be a part of Carbon Action Initiative explained in the subsequent text.

Carbon Action Initiative

Carbon Action is an investors' initiative focusing on motivating companies to take measures to reduce emissions and expand pro-environmental behaviour in general that are promising a return on investment. CDP Carbon Action is financed by 304 investor signatories, detaining US$ 22 trillion in investment and coordinated by the Principles for Responsible Investment.

The investors ask the companies in heavy-emitting industries to take three specific actions in response to climate change: set targets, reduce emissions, and generate the return on investment. The Carbon Action request is sent as a letter to the Chair of the Board each year. In 2015, the Carbon Action request went to over 1300 companies across 17 high emitting industries.

This program is two-sided. The companies can take the advantage of it in a way that it helps them to generate positive returns through carbon reducing and energy efficiency projects and so build long-term sustainable businesses. On the other side, signatory investors can better understand company carbon management and energy efficiency initiatives and improve risk management in areas including regulation, operations, fiduciary duty and reputation.

Supply Chain member

Apart from investors, also corporations have an opportunity to be a member of the Carbon Disclosure Project. CDP proposes companies to become either a Supply Chain member or Reporter Service member. The first membership we explain in the following paragraphs, and the second type of membership gets closer attention in section 3.3.2.

As a Supply Chain member, company has access to the Supply Chain Program. In 2015, CDP counted for 89 Supply Chain members representing combined purchasing power of over US$2 trillion. The membership gives access to the supply chain disclosure platform, providing information about their suppliers' approach to climate change or water management.

Moreover, members can request their suppliers to answer CDP's questionnaire. The requested suppliers get CDP's support in answering, but also the help in improving their performance. CDP proposes the analysis of member's environmental data and advice the implementation of the strategies. In 2015 CDP collected climate change and water information from over 4000 companies.

Cities

As already mentioned, cities have a possibility to measure, monitor and manage their impact on the environment through the CDP's cities program. The program exists since 2006, and during the five years of its existence, CDP collaborated with over 500 cities to manage over 2 billion metric tonnes of greenhouse gas emissions, which estimate protections of about 621 milliards of people by cities that are taking the lead on climate adaptation.

By participating in the program, cities has an opportunity to detect and manage their risk and increase resiliency through more than 4800 activities to reduce and adjust to climate change.

CDP with governments & policymakers

As already mentioned, the CDP collaborates with governments, policymakers and international institutions in order to help them in areas such as mitigation and adaptation to the climate change. The aim is to support the green economic growth, by giving assistance to governments and providing tools that lead to the creation of more sustainable policies and regulations, by encouraging governments to adopt regulatory standards for disclosure of environmental data and support governments in designing and implementing corporate reporting systems.

CDP provides governments with researches and analyses based on the unique data on environmental issues. Moreover, it informs policymakers about the efforts, actions and impact of the corporation and cities with respect to the environmental issues. CDP also advises regulators on formulating policy, supports governments in designing and develop tailored programs hand in hand with them.

Alliances

The data and programs that CDP proposes are of high quality. In order to be on the top of the research, and to propose to the firms, investors and institutions the best solutions, the CDP is collaborating with a multitude of other organisations and institutions, creating a number of mutually profitable partnerships.

CDP claims that: *"Collaboration is crucial to achieve more sustainable economies.*[22]*"* CDP supports many different initiatives and has strong alliances around the world with policy-makers, researchers, academic institutions, standard setters, other Non Governmental Organisations. As an example, we can name the Global Reporting Initiative, UN Environment Programme, UN Global Compact, Greenhouse Gas Protocol. All these organisations are described in sections 3.1 and 3.2. Moreover, CDP is being part of the Caring for Climate Initiative[23].

3.3.2 Corporate reporting to Carbon Disclosure Project

From the firm's perspective, CDP's main objective is to help companies to take action toward a more sustainable world. Reporting companies get help in building environmental strategies that improve the management of environmental risk. That is, the focus is on reduction of CO_2 emissions, use of energy, investment in new lower pollution production, improvement of supply chain and many other pro-environmental tactics.

CDP believes that companies that are aware of the scope of their environmental risk can better manage the environmental strategies and improve their "green" footprint. CDP is convinced of the crucial importance of firm's carbon disclosure transparency and the necessity to provide the environmental information to the decision makers in order to drive the appropriate action in sustainable development.

On one side, the corporations are required either by investors (CDP investor initiative) or customers (Supply Chain members) to report their data. By this channel, the companies do not have to pay participation fees. On the other side, each company also has the opportunity to take the initiative to report their data voluntary and become a Reporter Services member. Reporter Services membership gives organisations data, support and insights to reduce emissions, enhance water stewardship and improve business performance. Companies can benchmark their performance against peers and identify material risks.

CDP proposes four main programs focusing on firms: climate change, water, forest or supply chain. These programs are described in this section. Moreover, we also present the Climate Performance Leadership Index, which is a CDP tool to reveal which companies around the world are doing the most to combat climate change. And we conclude by presenting a special CDP project, so-called Climate Disclosure Standards Board, that attempt to integrate the climate change-related information into the main financial reports.

[22] Source: Alliances. Retrieved August 01, 2016, from https://www.cdp.net/en-us/ournetwork/pages/alliances.aspx.

[23] Caring for Climate is a CEO-level business initiative that promotes climate leadership and transparency, founded in 2007 by UN Environment Programme, UN Global Compact, UN Framework Convention on Climate Change.

CDP programs focusing on firms

Climate Change

CDP's climate change program's target is the reduction of companies' greenhouse gases emissions and the mitigation of the climate change risk. As a part of the program, the corporations measure, manage and disclose their greenhouse gas emissions and climate change data. The main benefits of being part of the program are the increased transparency, assessment of the climate change management, evaluation of available business opportunities, increasing efficiency and reduce unnecessary costs.

Water

The CDP's water program main objective is to mobilise action on corporate water management in order to secure water resources and alleviate the global water crises. The process of responding to the water questionnaire helps corporations to better understand the risks and opportunities associated with water scarcity and other water-related issues. Business reporting to water program gets similar benefits as one of the Climate Change programs and can be transparent, better manage the risks, discover the opportunities.

Forest

CDP's forest program intends to manage companies' impact on the deforestation risk and as a consequence regulate the land use change for agriculture as being the main driver of deforestation. The program assists companies to disclose the four forest risk commodities most responsible for deforestation globally. Reporting the forest-related information helps firms with communication with investors or stakeholders, managing internal risk, discovering new opportunities, encourage collaborations.

Supply Chain

CDP's supply chain program objective is to achieve sustainable supply chain management for firms and their suppliers by optimising the risks and opportunities that climate change puts to the globalised supply chain. More details about the program is in section 3.3.1.

Climate Performance Leadership Index

Since October 2010, CDP ranks companies with high-quality disclosure as top scoring companies in the Climate Performance Leadership Index (CPLI). The leading firms with high-performance score figure on the "Climate or Water A list". These companies are gaining competitive advantage and commercial benefits over their competitors and can potentially count on more investors or government help. For many investors, the CPLI has become a standard, and they may expect the companies not only be reporting to the CDP but also to have a certain index position.

CDP works with a number of partners to deliver the scores for all responding companies. Moreover, only the top-scoring companies that have made their response public will be eligible for recognition as leaders. If a company requires the response to be non-public, the response may still be scored, and that score may be published. This makes from the CDP an organisation, which motivates the reporting companies to provide data of good quality. But also discourages the companies to report their climate change-related data, under a fear of getting an unsatisfactory rating.

Climate Disclosure Standards Board

Climate Disclosure Standards Board is CDP's special project focusing on integrating climate change information into private sector's financial reporting. CDP claims *"In short, it is about linking financial and climate change-related reporting to provide policy-makers and investors with clear, reliable information for robust decision making.*[24]*."*

It does not try to create new reporting standards but adopts existing standards and practices including the Greenhouse Gas Protocol and International Financial Reporting Standards and others. Moreover, it works as a collaborative forum to improve these standards and practices, ensures transparent markets and encourages standardised approach of reporting the climate change data.

[24] Source: Special projects. Retrieved August 05, 2016, from https://www.cdp.net/en-US/OurNetwork/Pages/special-projects.

Part II

Empirical part

Chapter 4

Research question, data and model implementation

As we are going to start the empirical part of the investigation, it is the time and place to present the research program.

In this chapter, we first do a short literature review of firms' environmental evaluations. The first section also sets up the hypotheses and expectations that we have with respect to the Carbon Disclosure Project (CDP) evaluation. The second section talks about our unique database used in the empirical part. We present not only the building process but also the variables and descriptive statistics. The third section of this chapter introduces the methodological part of our study. We present the model and the application of the synthetic control method to our study. We also establish the inference tests used to evaluate the significance of the results. The last section is dedicated to the implementation of the model with the statistical program R, that we used to run the study. We briefly introduce the package "Synth", but we focus on the presentation of the code and showing the results of the most important functions, to help to present the results of our analysis in the following chapter.

4.1 Literature review and main goals of the study

As already mentioned, we intend in our study to evaluate the introduction of one of the environmental reporting standards at the business level. In this section, first of all, we present a brief literature review of firms' environmental evaluations studies done by other authors. Note that it is just an introduction and not an exhaustive list of all studies. Next, we develop the research question. More precisely, we explain why we evaluate the Carbon Disclosure Project with the synthetic control method, one of the program evaluations approaches. We also shortly introduce the study, and we set up the expectations and hypotheses. Note that the details of the model and the application of the method are explained in the section 4.3.

4.1.1 Brief literature review of firms' environmental evaluations

We are not the first to evaluate the firm's environmental disclosures, but other studies have a slightly different emphasis on the problematic. Already in early 90's Wiseman (1982) assesses the environmental disclosures made in corporate annual reports, and reveals the poor quality of reported data. Other studies focusing on the quality of disclosed data, as for example Dragomir (2012), or Andrew and Cortese (2011), found similar deceiving features of disclosed environmental information.

Different categories of findings in environmental accounting are for example due to Al-Tuwaijri et al. (2004), or Clarkson et al. (2008). These studies found a positive association between environmental performance and the level of environmental disclosure. Nevertheless these articles centre more on building and evaluating the so-called disclosure index and less on the actual policy evaluation.

Luo and Tang (2014) is the closest study to ours since they evaluate the Carbon Disclosure Project. But again, their focus is on the relationship between the degree of disclosure and carbon performance, rather than on the program evaluation itself. They conclude that the firms' voluntary carbon disclosure in the CDP is indicative of their underlying actual carbon performance and that the firms with good performance are likely to disclose more to distinguish themselves for investors and other stakeholders. The limit of their research is that the analysis is merely a snapshot of reporting practice over a single year.

Finally, Abrell et al. (2011) assess the impact of the European Union Emission Trading System (ETS) using firm-level data. This study is very close to our analysis, with the difference being their focus on a different program and the use of another method to evaluate the effect. Even though they found positive results of the program on firm's emissions, they conclude that the result has to be interpreted with caution, as the counterfactual built (similar companies that are not part of EU ETS) is not of very good quality.

Comparing to all these studies, we bring a new light to the evaluation of the CDP over a longer period of time with a more reliable method to assess the effect of the program.

4.1.2 Research questions

This section develops our frame of hypotheses and research questions. First, we present the objectives and a brief description of our study. Then we set up the expectations and hypotheses that we have for the Carbon Disclosure Project assessment. The table 4.1 briefly introduces the concept of the research questions and the expectations that are presented in more details on the following pages.

Research questions	Theory	Identification of the variables	Expectations
Main: Is there a positive impact of the Carbon Disclosure Project on the participating firms?	The impact of the environmental policy is a typical causal effect evaluation. We use the synthetic control method to solve the assessment of the treatment effect.	The outcome variable is the carbon dioxide emissions per firm. The confounding variables are different firms' characteristics.	We expect a positive effect of CDP on the firm's emissions.
Subsequent: Is there a difference of the impact on the international level, between European Union, United Kingdom, United States?			We do not expect a big difference between the geographical regions.
Is there a difference of the impact between the sectors of activities?			We can not predict the outcome of the comparison between the sectors.

Source: Author's elaboration.

Table 4.1: Research questions, variables and expectations

Objectives and theory

The objective of the study is to evaluate the impact of the Carbon Disclosure Project on the firm's greenhouse gas emissions. Moreover, we want to compare the results of the assessment on an international and sectoral level.

The impact of the CDP is a causal effect that can be measured by a program evaluation method. In our case, the potential outcome (see section 1.2.1) is the carbon dioxide emissions of the firm, and the treatment effect is the comparison of the carbon path of the firm that participates to the Project and the carbon path of the same firm that do not participate to the CDP. Comparing the carbon path before and after the company started to report to the CDP would be a naive solution, as it does not take into consideration the business as the usual evolution of the firm. Consequently, we have to reproduce the potential outcome of the treated firm in case of no-participation to the program and this control unit is created, as already mentioned, by using the synthetic control method.

Identification of the variables

To measure the impact of the green policy, the outcome variable that we selected is the yearly CO_2 emissions of each firm. Evidently, the CO_2 emissions are also influenced by other company characteristics and not only by the participation to the CDP. Also, we have to collect also other information on the firms. The variables are described in the section 4.2.

Expectations and hypotheses

We do have several expectations as predicted results of our study. First of all, we expect to have a positive impact of the CDP on the carbon path. That is, decreasing CO_2 after the company started to report the environmental data to the project. This expectation comes from the hypothesis, that the CDP has a positive incentive power on the company to diminish their emissions.

Moreover, our data contains companies from the three regions: the European Union, the United Kingdom and the United States. The driving factor for this choice is that we consider these different regions as being in the same economic development. Therefore, if there is a shock to one of these economies, as an economic crisis, all of these interdependent regions will be hit, so there should not be an external shock influencing the main study variable. As a result, we do not expect big differences with respect to the number of positive treatment effects between the regions. This expectation comes from the hypothesis that the three regions have a similar degree of economic development, but also have similarities in corporate social responsibility policy, which influence the degree of emissions.

Additionally, our data are divided into nine different sectors. The first reason behind this is that the firms from different sectors have a different behaviour which influences a number of their emissions. As for example, the firm from the industrial sector will have much higher emissions than the firm from the financial sector. The second reason is that firms are influenced by sectoral shocks, which reverberate on the companies from the same sector. We suppose that this sub-classification will help to build an appropriate synthetic control that would reproduce the behaviour of the treated unit in case of non-treatment.

Finally, with respect to the synthetic control method, we suppose that the assumptions 4 (First SCM assumption) and 5 (Second SCM assumption), presented in the section 2.2.1, are satisfied.

4.2 Database and descriptive statistics

For our study we are using a unique database that we built by adding several firm's characteristics to an initially requested database provided by South Pole Group[1]. Based on particular companies' specifics, we were then able to select the suitable treated and control groups. In this chapter, we describe the creation of the database, the variables and we provide some descriptive statistics.

4.2.1 Database creation

Once the objectives of our research had been set, we collect the data on the company's CO2 emissions as well as on additional firm's characteristics. This was a very challenging step as the information on the amount of greenhouse gases produced by the companies are not easily available. We got in contact with South Pole Group concerning the existing data on the company's emissions. The South Pole Group provided the data for 119 potential companies containing their names, stock ticker symbols and CO2 emissions for the period from the year 2005 to 2013.

We created several variables, NAME, CDP_IN, CDP_YEAR, which are briefly described in annexe in the table A.1. We found the information for all companies in the official CDP database[2]. We discovered that all the companies were participating to the CDP program and that most of the participations started in the first years of the CDP foundation in 2003. The problem was that we needed to create two pools of companies: treated and control. For the treated companies we needed observations from a few years prior to, and post treatment. For the control companies, we needed companies that did not participate to the CDP program. None of these requests was satisfied, so these companies were deemed not appropriate for our research.

As a result, we needed to constitute a new database. Hence new data was requested from South Pole Group. We subsequently received the names of 1500 potential companies, and as for the previous database, we collected the information on the same variables: NAME, CDP_IN, CDP_YEAR. At first glance, we verified that there were participating and non-participating companies to the CDP with respect to our requirement. Note that most of the companies, even the one non-participating to the Carbon Disclosure Project, were present in the CDP database, so we had a unified source of information.

As already mentioned, our goal was to create a database containing companies that did and did not participate in the Carbon Disclosure Project, respectively the treated and control units' pools. Moreover, in order to measure the treatment effect, we had to get information on the emissions few years before and few years after the firm signed to the CDP. As a consequence, we decided that the treatment year will be 2009 or 2010, which will allow covering four to five year before the treatment and three to four years after the treatment.

[1] South Pole Group is a specialist provider of climate action solutions that is, among other solutions, offering consulting services, data and products for investors in the area of assessing investment climate impact.

[2] Source: Results - responses. Retrieved August 18, 2016, from https://www.cdp.net/en-US/Results/Pages-/responses.aspx.

Another important aspect was to create a donor pool with units that are good potential adepts for a synthetic control. Remind, that a good synthetic control is as similar as possible with its treated unit. Thus we not only concentrated on firms from the three geographic regions that do have similar pro-environmental behaviour and economic development, that is the European Union, the United Kingdom and the United States; but also we intended to equally cover all economic sectors. Moreover, in order to select the firms for the analysis, we added the following variables: COUNTRY, SECTOR, INDUSTRY_SECTOR, SUB_INDUSTRY, CLIMAT_CDP, WATER_CDP, SUPPLY_CHAIN_CDP, FOREST_CDP. The variables are described in the annexe in the table A.1.

We found the information for all companies and then started the selection process. First, we selected all the companies that participated to the CDP and we formed the first "treated" pool. From this pool we picked only the firms from the three selected geographic regions, the EU, UK and US, which signed to the CDP in 2009 or 2010. For the donor pool, we got exclusively non-participating companies coming from the three mentioned geographic regions. Moreover, we also checked that each sector from the treated pool was represented in the donor pool. So, by this process, depending on the firm's characteristics, we have chosen 300 companies. In the end, after a closer analysis, only half of them were kept.

To complete the database, we required from South Pole Group different companies characteristics as the source of the reported CO2 emissions, revenues, gross profit, the cost of goods sold, fixed assets and a number of employees. We also added two additional variables to the database, the share price and the return on investment that are also the variables supposed to be highly related to the companies environmental activities. These two variables were collected from the database Thomson Reuters. All the variables are described in the table A.1.

As the primary database had missing data, we needed to complete the missing values via the companies annual reports, or other verified sources as CDP database[3], Thomson Reuters, Statista, YCharts, companies' annual reports or CSR report. In some cases, values needed to be aligned to the new officially published information. In cases where it was not possible to verify suspicious values or to complete missing data, the company was deleted from the database. Eventually, we collected fully complete, verified information on 135 companies.

Note that for the later analysis we needed to transform the original transversal structure to a panel database. To do so, we used the R packages "reshape" (Wickham (2007)) for the purpose of changing the structure of the data and the package "gdata" Warnes et al. (2014) to rename and remove the variables. We also reduced the number of the variables from 77 to 22, as we had the observations per year in panel data. Certain variables remained the same, other changed. The variables and their description of the reshaped panel database figure in the table 4.2.

4.2.2 Variables description

For our analysis, we are using a database which has 135 observations (firms) and contains 22 variables observed over a period of 9 years, from 2005 to 2013. All variables from panel database are

[3]Source: Home - CDP. Retrieved November 02, 2016, from https://www.cdp.net/.

described in table 4.2, and few variables that exist only in the transversal database are presented again in the table A.1. Note, we had several variables that served as identification variables, although important for us, they do not get any attention in the description. In this section, we describe the selected principal variables into more details.

Variables	Description
ID	Company's identification number (numeric);
NAME	Company's name (nominal);
YEAR	Year (numeric);
CDP	Indicator variable defining if the company is reporting to the CDP (0: not reporting, 1: in 2009; 2: in 2010) (numeric);
COUNTRY	Company's headquarter (nominal);
SECTOR	Company's sector (nominal);
INDUSTRY_SECTOR	Company's industry (nominal);
SUB_INDUSTRY	Company's sub-industry (nominal);
CLIMAT_CDP	Indicator variable defining if the company is reporting to the Climate Change program (0: No; 1: Yes)(numeric);
WATER_CDP	Indicator variable defining if the company is reporting to the Water program (0: No; 1: Yes) (numeric);
SUPPLY_CHAIN_CDP	Indicator variable defining if the company is reporting to the Supply chain program (0: No; 1: Yes) (numeric);
FOREST_CDP	Indicator variable defining if the company is reporting to the Forest program (0: No; 1: Yes) (numeric);
GHG	Company's greenhouse gas emissions in metric tons (numeric);
S	Source of the reported company's greenhouse gas;
R	Company's revenue in mio Swiss fancs (CHF) (numeric);
GP	Company's gross profit in mio CHF (numeric);
COGS	Company's cost of goods sold in mio CHF (numeric);
FA	Company's fixed assets in mio CHF (numeric);
EMP	Company's number of employees (numeric);
P	Company's share price in CHF (numeric);
RI	Company's return on investment in CHF (numeric);
KL	Company's capital-labor ratio (numeric);
GHG_EMP	Company's greenhouse gas emissions in metric tons per employee (numeric).

Source: Author's elaboration.

Table 4.2: Variables in the panel database

CDP, CDP_IN

The variable CDP, which figures in the panel database, is a categorical variable, defining whether the company is reporting to the CDP. It takes three values: 0 for non-participating companies, 1 and 2 for participating companies that signed to the CDP in 2009 or 2010 respectively. In the transversal database, this variable is called CDP_IN and takes values 1 for participating companies and 0 for non-participating companies, without any reference to the year. This information was handled by the variable CDP_YEAR, described in the next section.

The variable CDP_IN, in the transversal database, was built in two steps. First, we checked if the company is contained in the CDP database. Note that with the exception of one observation, all the selected companies figured in the CDP database. The second step was to verify the reporting status in the CDP database. The six possible reporting statuses were:

- Answered questionnaire: answered some or all of the questions in the questionnaire;
- Declined to participate: declined to participate in the project;
- Information provided: provided information relevant to the questionnaire; did not answer the questionnaire;
- No response: did not reply to CDP regarding the request;
- Not in CDP: not in a CDP sample for the year specified;
- See another: the response is covered by another company, usually the parent company.

The companies that answered the questionnaire in some year t and all the following years took the status 1. If the company did not answer the questionnaire for just one of the years after the year t, we still considered the company to be part of the program. Companies with a discontinuity in their answers, or with reporting status "See another", were rejected from our database, and were not even considered as non-treated companies. We considered the company as non-participating, with the status 0 if one of the following conditions were satisfied: company was not in the CDP database and so we considered that it does not participate to the CDP program; company declined to participate; company only provided the information without answering the questionnaire; company did not provide the response.

Note that all companies with value 0 for the variable CDP_IN in the transversal database took the same value 0 for the variable CDP in the panel database. In order to be considered as a treated unit, and so have values 1 or 2 in panel database, the company needed to have completed the questionnaire for the treatment year $T+1$ (years 2009 or 2010 - see variable CDP_YEAR), and also all the following years. The information on the year came from the transversal database. Firms with other CDP_YEAR than 2009 and 2010 were not considered in our analysis and so do not figure in the final database.

CDP_YEAR

The variable CDP_YEAR appeared only in the transversal database but helped to build the variable CDP in the panel database. The variable provides the information on the year when the company started to report to the CDP. It does concern only the years 2003 to 2013, as the CDP exists only since 2003, and for the year 2014, the data were not yet published. If the company does not report to the CDP program, the variable takes value NA.

In order to create this variable, we search in the official CDP database whether the company does exist. If it was the case, we verified the year of the first report to one of the four CDP's programs (Climate change, Water, Supply chain, Forest; cf., section 3.3.2).

As already mentioned, this variable was one of the selection's variables, and the final database contains only observations with values equal to 2009, 2010 or NA. By default, the variable CDP_IN in the transversal database is the filter variable and already defined the reporting status and conditions for variable CDP_YEAR. That is why in the panel database the variable CDP contains both pieces of information as there are only three possible values. But remember that when selecting the observations from the transversal database we had more than 1600 firms to choose from.

COUNTRY

The variable COUNTRY defines the country where the company's headquarters are based. The values for this variable were taken from the CDP database. This variable is very important because the origin of the company mostly defines company's politics including the sustainability. As already mentioned, the final panel database contains only the three values: European Union (EU), United Kingdom (UK), and United States (US).

We have selected these regions not only because of their similarities in economic development but also and especially because of the similarities in corporate social responsibility policy. We can name the most common regulations in these regions, which are the EU Emission Trading System, the UK Carbon Reduction Commitment Energy Efficiency Scheme and the US Environmental Protection Agency's Mandatory GHG Reporting Rule. UK is not purposely included in the EU, because of its specificity in sustainable development strategy. More detailed information about the European, British and American low-carbon politics are presented in the section 3.2.2.

SECTOR, INDUSTRY_SECTOR and SUB_INDUSTRY

The variable SECTOR, INDUSTRY_SECTOR and SUB_INDUSTRY specify the company's sector, industry and sub-industry. The coding was defined by Global Industry Classification Standard (GICS). The GICS structure consists of 10 sectors, 24 industry groups, 68 industries and 154 sub-industries. We found the values for the three variables in the CDP database.

The variable SECTOR contains the following values: Consumer Discretionary (CD), Consumer Staples (CS), Energy (ENGY), Financials (FINA), Health Care (HC), Industrial (INDU), Information Technology (IT), Materials (MATR), Telecommunications (TC), Utilities (UTIL). We describe the sector classification in the annexe A.2. Note that we had only one observation in the telecommunication sector. Thus we combined it with Information Technology and created sector called Information Technology and Telecommunication ITTE. For more information on GICS classification please see the CDP Technical Note on Global Industry Classification Standards [4] Carbon Diclosure Project (CDP) (2014a).

CLIMAT_CDP, WATER_CDP, SUPPLY_CHAIN_CDP and FOREST_CDP

The variables CLIMAT_CDP, WATER_CDP, SUPPLY_CHAIN_CDP, FOREST_CDP define the year the company began reporting to the CDP's Climate change, Water, Supply chain or Forest programs, respectively. This concerns only the period between $2003-2013$, and the variable takes value NA if the company does not report to one of the CDP's programs. Company's reporting continuity to the program is a necessary condition to consider the firm being part of the program.

We can sum up the properties in the following manner:

- *CDP's climate change program* target is the reduction of companies greenhouse gases emissions and the mitigation of the climate change risk;
- *CDP's water program* main objective is to mobilise action on corporate water management in order to secure water resources and alleviate the global water crisis;
- *CDP's supply chain program* objective is to achieve sustainable supply chain management for the firms and their suppliers by optimising the risks and opportunities that climate change and water pose to the globalised supply chain model;
- *CDP's forest program* intends to manage companies impact on the deforestation risks and as a consequence regulate the land use change for agriculture as being the main driver of deforestation.

GHG

The variable GHG gives the values of company's greenhouse gas or CO2 emissions (used as a proxy) for the years $2005-2013$. The emissions were mostly provided by South Pole Group. South Pole Group got the information on the CO2 emissions either from different reports, or they did estimate them via different appropriate models. The origin of the reported values is given by the variables S - source presented below.

[4] Source: CDP technical note on Global Industry Classification. Retrieved November 2, 2016, from https://www.cdp.net/Documents/Guidance/2014/cdp-technical-note-gics-2014.pdf.

In order to calculate the amount of emissions released into the environment by the company, the Greenhouse Gas Protocol, also used by CDP, suggests reporting the values from different sources: direct and indirect emissions. Furthermore, the Greenhouse Gas Protocol specifies: *"Direct GHG emissions are emissions from sources that are owned or controlled by the reporting entity. Indirect GHG emissions are emissions that are a consequence of the activities of the reporting entity but occur at sources owned or controlled by another entity. The GHG Protocol further categorises these direct and indirect emissions into three broad scopes:*

- *Scope 1: All direct GHG emissions;*
- *Scope 2: Indirect GHG emissions from consumption of purchased electricity, heat or steam;*
- *Scope 3: Other indirect emissions, such as the extraction and production of purchased materials and fuels, transport-related activities in vehicles not owned or controlled by the reporting entity, electricity-related activities (e.g., T&D losses) not covered in Scope 2, outsourced activities, waste disposal, etc.[5]"*

The reported values in our database contain only Scope 1 and Scope 2 emissions.

Note that we verified all suspicious values having big differences between GHG's emissions within the years. If any pieces of information that helped us to correct the difference was found, we adjusted the GHG's emissions. If we still had doubts with respect to the reported values, we deleted the firm from our database.

S

The variable S defines the source of the reported GHG's emissions for the years 2005 to 2013. Each of the values is associated to the corresponding value of the variable GHG. The variable was provided by South Pole Group, with certain adjustments depending on corrections of the variable GHG.

The variable source takes the four following values:

- APROX: approximation by the model;
- CDP: carbon disclosure project database;
- CSR: corporate social & sustainability responsibility report;
- REP: various reports (may include CDP or CSR reports).

[5]Source: Greenhouse Gas Protocol - FAQ. Retrieved October 13, 2016, from http://www.ghgprotocol.org/calculation-tools/faq.

R, GP, COGS, FA, EMP, P, RI, KL, GHG_EMP

The following variables: R, GP, COGS, FA, EMP, P, RI, KL, GHG_EMP, report different company's characteristics. Apart of the variables P, RI, they were provided by South Pole Group and we have completed the database in case of missing data. The financial data are in Swiss Francs (CHF). Note that the data collected in different currencies were converted in Swiss Francs with respect to a specific year[6]. The two variables: P, RI, were collected via Thomson Reuters. We describe the variables in the upcoming paragraphs.

The variable R defines company's annual revenue in million CHF. The Sales/Revenue/Turnover represent the total of operating revenues less various adjustments to Gross Sales. The adjustments are: returns, discounts, allowances, excise taxes, insurance charges, sales taxes, and value added taxes (VAT). Moreover, this variable includes revenues from financial subsidiaries in industrial companies if the consolidation includes those subsidiaries throughout the report, and subsidies from the federal or local government in certain industries (i.e., transportation or utilities). Additionally, the variable excludes inter-company revenues and revenues from discontinued operations.

The variable GP gives companies gross profit in million CHF respectively. Gross profit, as defined by South Pole Group, is a company's residual revenue after selling a product or providing a service minus the costs associated with the production or service. In other words, it is a company's revenue minus its cost of goods sold. Concerning financial companies, they do not have figures on the cost of goods sold, so by default, it was not possible to have the gross profit numbers. In this case, we opted for the operating income to replace the missing values of the gross profit, which is the revenue minus the operating costs.

The variable COGS delineates company's annual cost of goods sold in million CHF respectively. The definition for the cost of goods sold is specific to the sector or industry. The specifics also change as well within production or service companies. One of the definitions, from Investopedia, we used while collecting the missing data is: *"Cost of goods sold (COGS) is the direct costs attributable to the production of the goods sold by a company. This amount includes the cost of the materials used in creating the good along with the direct labour costs used to produce the good. It excludes indirect expenses such as distribution costs and sales force costs.[7]"* In order to define the COGS for the missing data, we either used the COGS directly reported by the company, or in case the company did not specify it, we used the standard definition of COGS in order to evaluate the right amount with respect to the specifics of the company. The financial sector does not report the cost of goods sold, so for these firms, we use operating cost instead of the cost of good sold.

The variable FA determined company's annual fixed assets in million CHF. It represents assets which are purchased for long-term use and are not likely to be converted quickly into cash, such as land, buildings, and equipment.

The variable EMP describes company's number of full-time employees.

[6]For exchange rate we used http://freecurrencyrates.com/.

[7]Source: Www.investopedia.com. Retrieved Octobre 21, 2016, from http://www.investopedia.com/terms/c/cogs.asp.

The variable KL is company's capital-labor ratio. It measures the ratio of capital employed to labour employed. We build this variable by making the ratio between the fixed assets and the number of employees, that is $KL = \frac{FA}{EMP}$.

The variable GHG_EMP represents the amount of the CO2 emissions produced by one employee in the firm. The variable was constructed by dividing the number of the emissions produced by the firm by the number of employees, that is $GHG\_EMP = \frac{GHG}{EMP}$.

The variable P defines the latest company's share price in CHF available from the appropriate market. It is the previous day's closing price from the default exchange except where more recent or real-time prices are available[8].

The variable RI describes company's return on investment in CHF. It is available for individual equities and unit trusts. This shows a theoretical growth in value of a shareholding over a specified period, assuming that dividends are re-invested to purchase additional units of equity or unit trusts at the closing price applicable on the ex-dividend date. For unit trusts, the closing bid price is used[9].

4.2.3 Descriptive statistics

As already mentioned, our database is unique and contains personally collected data with contribution from South Pole Group. For our analysis, we are using 135 observations on 22 variables observed over a period of 9 years, from 2005 to 2013. The variables are described in the previous section 4.2.2, and a brief explanation is given in the table 4.2. This section gives the descriptive statistics of our database. The table 4.3 presents the main quantitative information concerning the databases.

The names of all the observations are presented in annexee in table A.2, in addition, an example of one company is presented in table A.3. Out of the 135 companies, 73 do participate to the Carbon Disclosure Project, and 62 companies constitute the potential control units. As already mentioned, the observation period is nine years, from 2005 to 2009. Note that the time period is a very important parameter in our analysis, and so merits closer attention.

Ideally, we would like to use observations over a longer longitudinal scale, but the provided data by South Pole Group contains information from 2005 to 2013 only. Moreover, our main study variable, which is a company's greenhouse gas emission, could not be tracked for additional years. Even though we can easily find this information for the majority of the countries, for example, the World Bank provides the data going to 1960, the firms' level emissions are not so easily attainable.

The sustainable behaviour of firms received closer attention only in the last two decades, and since then the companies started slowly reporting their CO2 emissions. In the beginning, the reported values were highly inaccurate, and the firms needed a better guidance in how to collect and disclose the data. The companies did not have to wait long for this help, and many governments and private companies are now proposing a multitude of programs to this effect, as we explained in

[8] Source of definition: Thomson Reuters.
[9] Source of definition: Thomson Reuters.

Number of companies: 135
Number of participating companies: 73
Number of non-participating companies: 62
Period: 2005 - 2013
Regions: EU (48, 29, 19), UK (34, 16, 18). US (53, 28, 25)
Sectors: Consumer Discretionary (22, 10, 12), Consumer Staples (16, 12, 4), Industrials (36, 18, 18), IT & Telecommunications (14, 12, 2), Energy (8, 3, 5), Materials (11, 5, 6), Financials (12, 3, 9), Health Care (10, 7, 3), Utilities (6, 3, 3)
Note: In parenthesis you find number of observations for total, participating companies and non-participating companies respectively. Source: Author's elaboration.

Table 4.3: Global database in numbers

chapter 3. To our knowledge, there is no existing obtainable databases containing company CO_2 emissions for a longer period. Neither the companies themselves do not generally hold historical data on their emissions as it is a fairly new measurement, often neglected in the past. As Max Horster, Managing Partner of South Pole Climate Neutral Investments confirmed: *"It is not that companies are purposely hiding the correct numbers, they just did not put much effort into it."*

Another important information from table 4.3 is in the geographic regions. In total 14 different countries are represented: 48 from the European Union (excluded UK), 34 observations are from the United Kingdom, and 53 from the United States. The distribution between the treated and control units is quite equal, and we have always almost half of the observations of non-participating companies in each of the regions.

If we have a look at the variable sector, we see that the industrial sector is mainly represented with 27% of observations, followed by the consumer discretionary and consumer staples sectors with 16% and 12% observations. The rest of the sectors contains between 6 to 10% of companies. Moreover, the data contains information on 57 industries and 85 sub-industries.

Besides the table 4.3, the table A.4 in annexe contains other additional information on the variables. We can observe that 72 out of the 73 participating companies are in the CDP climate change program. Only 14 companies are in the CDP water program, 26 in CDP supply chain program and we see a smallest participation with only 5 companies in the CDP forest program. The last three programs were created after the pioneer climate change, respectively in 2008 the supply chain program, followed two years later by water program and in 2012 by forest program. The later founding of these complementary programs can explain the poor participation.

Another important part of the data descriptives is the distribution of companies between the sectors and countries. We find in annexe the cross-tables representing these statistics. Table A.5 in annexe presents the cross-table for all companies. More interesting is the distribution between participating and non-participating companies represented in tables A.6 and A.7 in annexe. We can see that the distribution of the companies within countries and sectors is quite similar and so none of the treated companies is without potential synthetic control, as the treated and control units are represented in all sectors and countries.

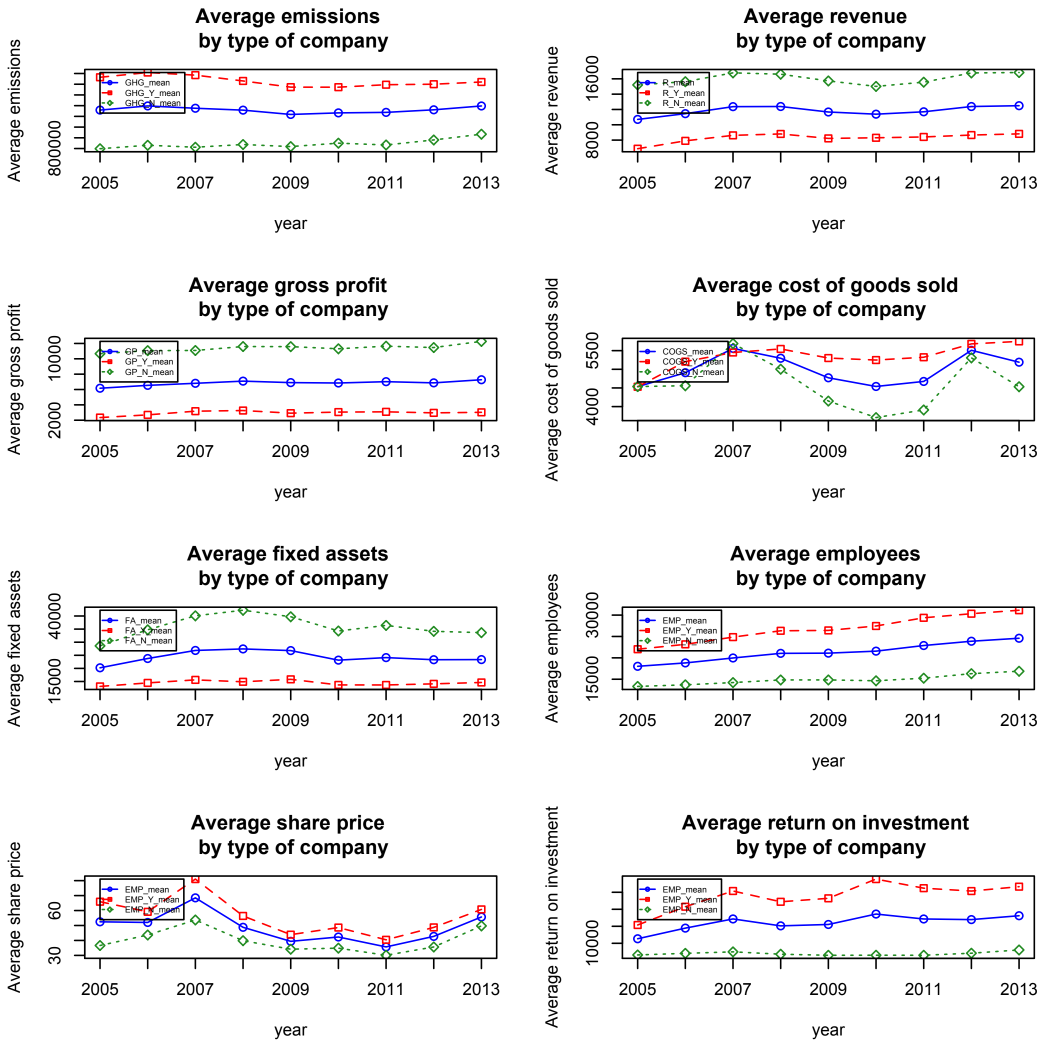
And another variable that needs a bit more attention is the variable source, S, and is reported in the table 4.4. We can see that most of the emissions for the year 2005 to 2007 were approximated by South Pole Group, starting with 97% of approximated data in 2005, still with 76% in 2007 and then radical dropping down since 2008. We end up with only 30% of approximated data in 2013. One aspect that can explain this number is that companies started to report to CDP in 2009 or 2010, 42 and 34 companies respectively, and the rest, meaning half of the total, do not report to CDP at all. Theses numbers can possible approve our theory on the fact that the companies started to be interested in their emissions only in last few years. The evolution of reporting can also give some credits to the hypothesis that the CDP participants have a bigger will concerning the transparency of reported CO2 emissions, compared to non-participants.

YEAR	APPROX	CDP	CSR	REP
2005	131	0	2	2
2006	116	2	13	4
2007	103	2	30	0
2008	85	4	44	2
2009	58	19	55	3
2010	44	18	70	3
2011	42	21	68	4
2012	36	29	68	2
2013	40	24	67	4

Source: Author's elaboration.

Table 4.4: Source of the reported company's emissions within the years

Figure 4.1 represents yearly averages and its evolution for different variables between years 2005 and 2013. We find the summary statistics for treated and control companies for each of the variables in table 4.5. First, let's analyse the figure. For each graph the blue line represents the average value for all companies, the red line is the average for participating companies, and in green, we have the mean for non-participating companies. The statistics in annexe show the number of observations, average, median, standard deviation, minimum and maximum. By observing these tables, we note that there is a big range for each of the variables and types of companies. The big difference is also remarkable between the mean and median. This shows the heterogeneity between the observations and the two pools (treated and control). After closer analysis, we found that different observations with very extreme values have a large influence on the mean. That is why we accompanied the average graphs with figure 4.2 which represents yearly median and its evolution for different variables between years 2005 and 2013.

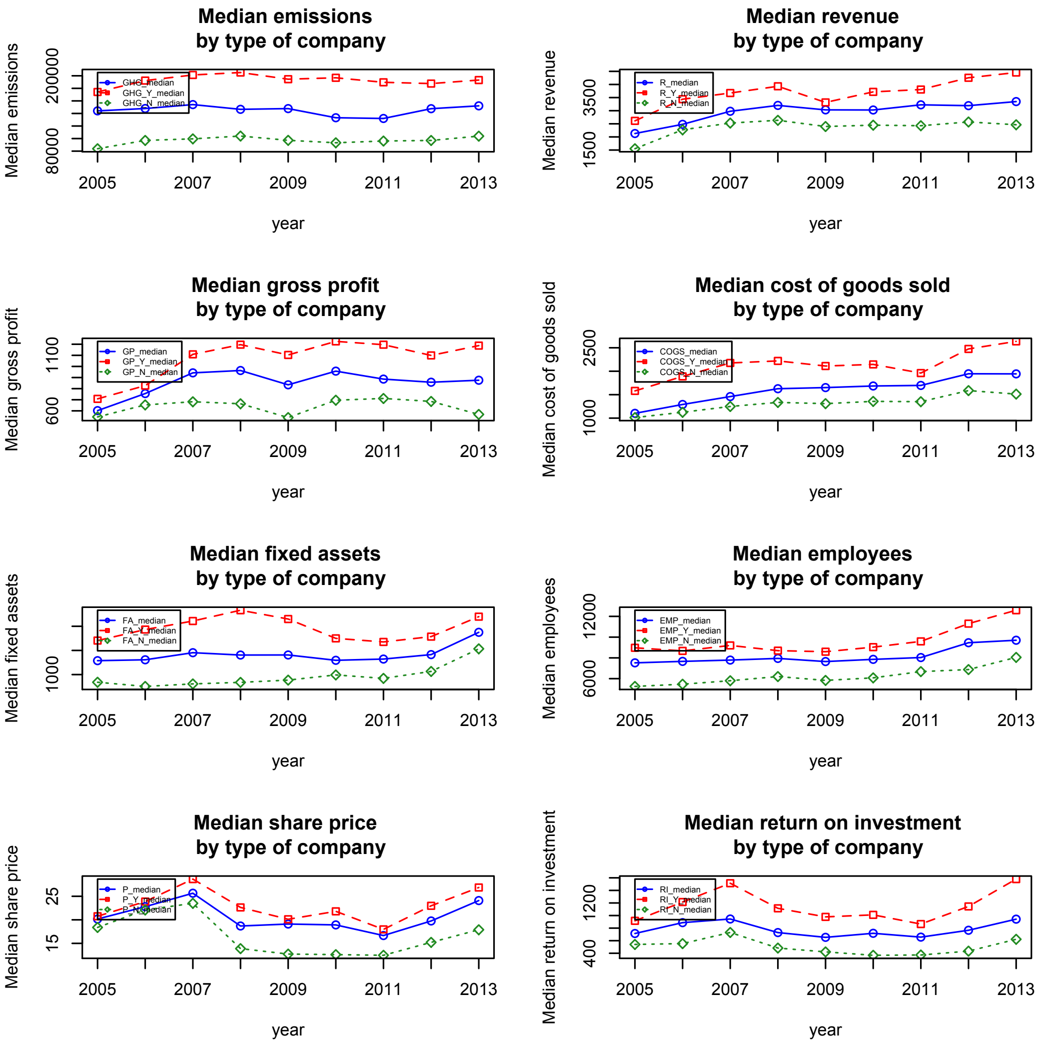


Source: Author's elaboration.

Figure 4.1: Graph of average statistics

We are mainly interested by companies' emissions. The other variables as revenue, gross profit, cost of goods sold, fixed assets, share price, return on investment and employees represent different characteristics of the companies. They will help us for normalising purpose and to build the synthetic control.

The graphics on figures 4.1 and 4.2 show gradual rise of all the variables from 2005 to 2013, and we notice the drop during the 2008 economic crisis. The variables that were not really influenced by the crisis are the fixed assets and number of employees. Concerning the fixed assets, companies could not react on that as quickly because there are very small degrees of liquidity for fixed assets. Concerning the number of employees, the main reason is that companies did cut the number of employees by serving a notice to the part-time, causal, daily or weekly hire employees in order to



Source: Author's elaboration.

Figure 4.2: Graph of median statistics

compensate the loss in production. As during the 2008 crisis the companies' production collapsed, the financial results of the companies were influenced as well. The revenues and cost of goods sold dropped, but gross profit conceived less influence. The average share price and return on investment seem to be also partially influenced by the crisis 2008.

Concerning the greenhouse gas emissions, they generally went up for all the companies. We observe a little drop of median CO_2 emissions for the participating companies after 2009 and 2010. On the opposite, the average CO_2 emissions went up after 2009 for participating as well as non-participating companies. But before we can get to any conclusion, we need to do more profound analyses to see whether this effect is due to the CDP project.

Variables	Mean	Median	Std. Dev.	Min.	Max.	N
CDP companies						
GHG	2055589	192362	6888017	1910	56739464	657
R	8290	3714	15061	86	108000	657
COGS	5337	2058	12261	0.16	103000	657
EMP	26785	9590	35561	67	171400	657
P	56	23	234	0.04	3117	657
RI	37559	1148	164030	7	1389152	657
KL	756718	145336	1910218	1376	11384492	657
GHG_EMP	168	13	587	1	7432	657
Non-CDP companies						
GHG	887478	96676	1727858	228	9842151	558
R	16013	2395	84223	15	6950000	558
COGS	4599	1248	11226	4	88012	558
EMP	14884	6206	29635	6	2470000	558
P	39	16	78	0.08	932	558
RI	3889	505	15652	6	193627	558
KL	1877658	129950	6505555	2370	58158299	558
GHG_EMP	217	15	673	1	6030	558

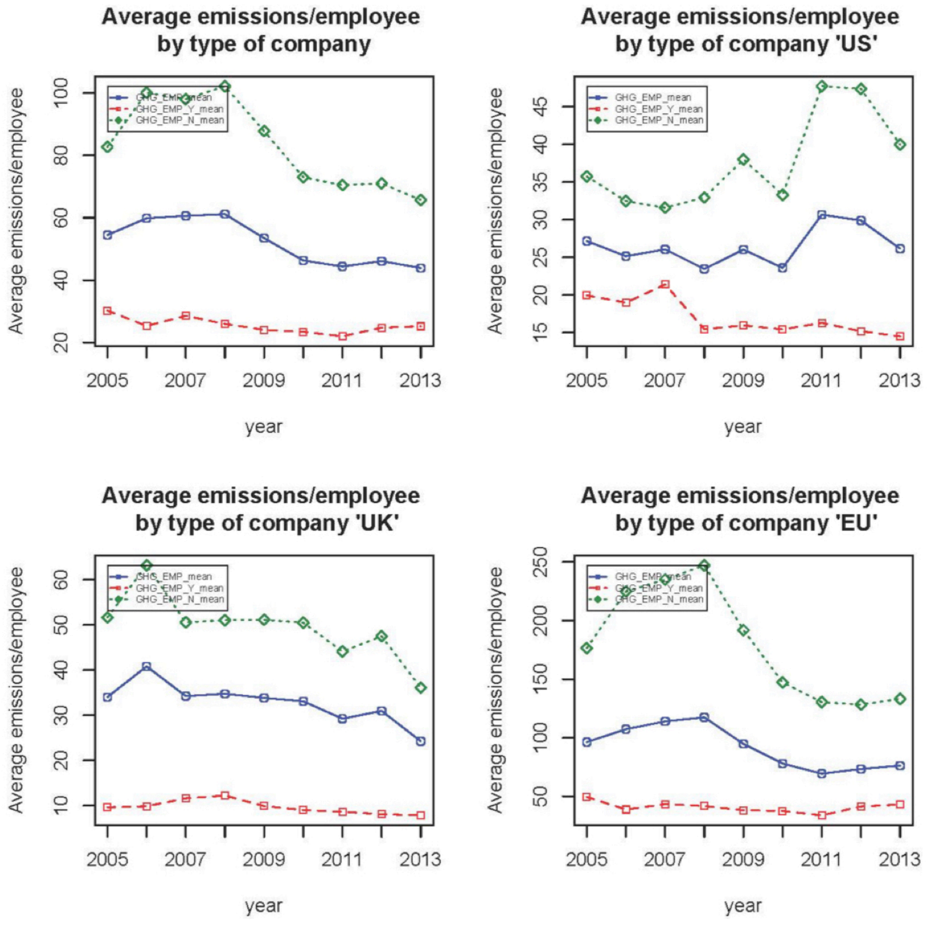
Source: Author's elaboration.

Table 4.5: Summary statistics (panel data on 9 years)

Table 4.5 reports the key descriptive statistics for our sample. We observe different values of the variable GHG for both participating and non-participating companies, with high average CO_2 emissions and extremely big range. On the other side, the CO_2 emissions per employee have much lower values and relatively to absolute emissions, this intensity measure considers the size of the firm and thus is more comparable across firms and also between different reporting periods. Thus we suggest considering the variable GHG_EMP as the measurement of carbon performance.

While exploring the data, we also did the same analysis by sector and by country (EU, UK, US). We remark that in general the conclusions were the same, except that the impact of the crisis was more or less pronounced. Also, the number of observations in each class is different, and due to this heterogeneity, the evolution might slightly differ from the general analyse that we have just presented.

Additional conclusions can be done from the detailed analysis per sector and per CDP participation for several variables (GHG, R, COGS, EMP, KL, GHG_EMP). The tables A.8 – A.16 in annexe contains the descriptive summary statistics for each sector. The first conclusion by analysing the tables is that the statistics are similar inside each sector and relatively different between the sectors, with smaller or bigger differences. The second conclusion is that we can divide the sectors into three categories with respect to the CO_2 emissions: heavy, medium or lighter emitters. In the first group, we qualify the energy, the materials and the utility sectors. They are characterised by very high Scope 1 and 2 emissions and the CO_2 emissions per employee, but also important capital-labor ratios. In the second group belong the consumer discretionary, the consumer staples and the industrial sector. These three sectors have relatively important CO_2 emissions, but with the high number of employees, their emissions per employee are relatively low. Note that it is better to check the median value for different variables, as the sectors contain some extreme values with respect to the emissions. The last group contains the financial, the health care, and the information technology and communication sectors. These three sectors have relatively low CO2 emissions and emissions per employee. They also have quite important number of employees and the capital-labor ratios. Concerning all other statistics, they are comparable between the sectors. Note, that the division of the sectors into these three groups also confirm the information provided in the Global 500 Climate Change Report 2013 by CDP (Carbon Diclosure Project (CDP) (2013)).



Source: Author's elaboration.

Figure 4.3: Average emissions per employee (company and regions)

The figure 4.3 presents the average emissions per employee without extreme values. The four quadrants show the nine years path not only for all companies but also per region. The green line denotes the non-participating companies, the blue one all companies and the red one the participating companies. These graphs represent only tendencies in an evolution of emissions per employee and cannot be used for the final conclusion to approve that there is a positive effect from the CDP program, even if the graphs would suggest otherwise. We also can observe the different evolution of the emissions per employee in each of the regions.

We also wanted to do the analysis by the size of the company, which means small, medium and large. This type of analyses is not possible, because with respect to the definition by European Commission[10] only 8 companies in 2005 and 4 in 2013 satisfied the definition of the small or medium company.

As a conclusion we must add that for our analysis, we are a bit of concern by the short time period of observations and as well by the 2008 crisis, that might influence our study.

4.3 Methodology

The objective of our study is to assess the effect of the Carbon Disclosure Project on the companies' carbon dioxide emissions. To do so, we use the synthetic control method presented in the chapter 2, one of the program evaluation methods that intend to assess the causal effect of exposure to a set of units to a program treatment on some outcomes.

In this section, we first explain the principal components of the model with respect to our case, such as the variables that constitute it. We further describe the way we estimate the optimal synthetic controls and the treatment effect, and we also present the alternative model that we considered for our analysis. In the second part, we talk about how we examined the results of the analysis. The third section presents the applied tests. And finally, in the last section we justify the selection of the model variables.

4.3.1 Model

The ultimate objective of the synthetic control method is to estimate the treatment effect, $\hat{\alpha}$, described by equation (2.5). In our case, the treatment is supposed to be the participation to the Carbon Disclosure Project. And we want to measure what is the effect of the CDP on the firms' greenhouse gas emissions. The program is assessed by the treatment effect, which is the difference between the observed emissions per employee of the company participating to the CDP and the estimated emissions per employee of its synthetic control company. To estimate the synthetic control, more precisely the weight representing the optimal synthetic control, we make use of the observed characteristics and the pre-treatment outcome of the units from the donor pool. The important elements of the model are described in the tables 4.6 and developed more in details bellow[11].

[10] Source: What is an SME? - Growth - European Commission. Retrieved November 01, 2016, from http://ec.europa.eu/growth/smes/business-friendly-environment/sme-definition_en.

[11] For more detail about the synthetic control, please check the section 2.2.1.

Research question:	The effect of the Carbon Disclosure Project on the firms' emissions;
Treatment:	Participation to the Carbon Disclosure Project;
Treatment effect:	The difference between the observed emissions per employee of the participating company and the estimated emissions per employee of its synthetic control;
Used method to estimate the treatment effect:	Synthetic control method;
Potential outcome:	Company's greenhouse gas emissions per employee (GHG_EMP)
Predictors:	Pre-treatment averages of the variables R, GP, COGS, EMP, KL, GHG, P and RI;
Special predictors:	Company's greenhouse gas emissions per employee for each pre-treatment year;
Donor pool selection:	For each of the treated unit we select the control units with respect to the sector characteristics of the firm (For more details check table 4.7);
Optimal choice of the weights for the control unit:	Data driven procedure, in particular the nested optimisation, to estimate the optimal weights $\mathbf{V}$ and $\mathbf{W}$ for the predictors and control units respectively;
Observed time period:	$2005-2013$;
Pre-treatment period:	$2005-2008$ or $2005-2009$;
Post-treatment period:	$2009-2013$ or $2010-2013$.

Source: Author's elaboration.

Table 4.6: Important elements of the model

Main elements of the model

For each treated firm we suppose a balanced sample of $J+1$ companies, indexed by $j=1,\dots,J+1$, that are observed at time period $t=1,\dots,T$. We suppose a positive number of pre-treatment periods T_0 and of post-treatment periods T_1, with $T_0+T_1=T$ and $1<T_0<T$. In our case, we observe the companies between years $2005-2013$. Therefore the total number of periods is $T=9$, the first period $t=1$ is year 2005, and the treatment years are either $T_0^{2008}+1=5$ or $T_0^{2009}+1=6$ for 2009 and 2010 respectively.

The potential outcome variable $\mathbf{Y}$, that measures the impact of CDP, is the CO2 emissions per employee (GHG_EMP). So, the outcome variable for the unit j at time t is:

$$Y_{jt} = GHG\_EMP_{jt}.$$

Without loss of generality, we assume that only the first company is exposed to the CDP and is uninterruptedly exposed to the program after some initial period. The rest of companies, which are not exposed, constitutes the donor pool of J control companies. Note that the number J changes from one treated company to another, depending on which sector the treated companies belongs to (see table 4.7). As only the first company from the sample is participating in the program, we denote by Y_{1t} the CO2 emissions per employee of the treated company at time t, and similarly by Y_{jt}^N, which is simply Y_{jt} $\forall j>1$, for the company without the participation to the CDP.

Moreover, in order to construct the synthetic control, we need to define the variables contained in the vector and matrix of the pre-treatment characteristics of the unaffected and controls units, $\mathbf{X}_1$ and $\mathbf{X}_0$ respectively (defined in equation (2.12)).

The variables, R, GP, COGS, EMP, KL, GHG, P and RI, are the confounding variables constituting the $(m\times T)$ matrix, where m, the number of the confounders, is equal to 8 and $T=9$. The C^l,

$l = 1, \dots, 8$, confounding variables constitute the $(r \times 1)$ vector of observed covariates $\mathbf{Z}_j$. In our case $r = l$, that is, for each confounder we have one specific linear combination of past values of the corresponding covariate. In particular, the covariates are the pre-treatment averages of the analogous confounder, that is:

$$Z_j^{L_l} = T_0^{-1} \sum_{s=1}^{T_0} C_{js}^{l}, \quad \forall l.$$

Thus the vector of predictors for the unit j is:

$$\mathbf{Z}_j = (\overline{R}, \overline{GP}, \overline{COGS}, \overline{EMP}, \overline{KL}, \overline{GHG}, \overline{P}, \overline{RI})'. \tag{4.1}$$

To complete the pre-treatment characteristics we define the special predictors. In our case they are the values of the CO2 emissions per employee for each pre-treatment year. Specifically, we define $M = T_0$ vectors $\mathbf{K}$ of order $(T_0 \times 1)$, and each special predictor is $Y_j^{\mathbf{K}_t} = Y_{jt}$ for $t = 1, \dots, T_0$. As a result, the values of the special predictors for the unit j are:

$$Y_j^{\mathbf{K}_1}, \dots, Y_j^{\mathbf{K}_M} = GHG\_EMP_{j1}, \dots, GHG\_EMP_{jT_0}. \tag{4.2}$$

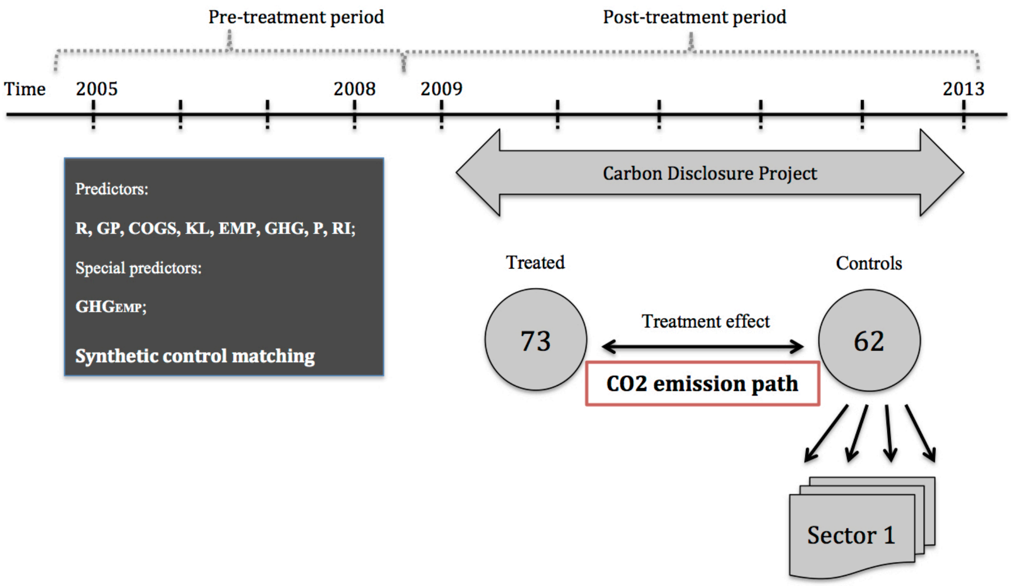
Based on the figure 2.1 from chapter 2.2.1, the figure 4.4 represents the application of the synthetic control method to our case (the example is for the treatment year 2009). In order to estimate the treatment effect, the first step is to use the predictors to estimate the synthetic control for each of the treated units during the pre-treatment period. The second step is to estimate the treatment effect during the treatment period. Let's first focus on the estimation of the optimal weights of the control unit.

Estimation of the optimal weights

For each of the 73 treated units, we selected a limited number of control units into the donor pool. The selection was based on the sector membership of the treated and control units. Table 4.7 gives the number of the treated units from each sector and the number of the control units constituting the donor pool. The last column of the table 4.7 shows the composition of the donor pool. Depending on the sector we analyse, we were obliged to enlarge our donor pool by selecting companies from another sector than the one of the treated unit only. The selection was always based on the characteristics of the sectors and the respective companies, that we already explained in the previous section 4.2.3.

Once we know the constitution of the donor pool and the values of the predictors, the next step is to estimate the $(J \times 1)$ vector of weights $\mathbf{W} = (w_2, \dots, w_{J+1})'$ such that $0 \leq w_j \leq 1$, for $j = 2, \dots, J+1$, and $\sum_{j=2}^{J+1} w_j = 1$. Remind that these weights give different importance to each of the control units that constitute the synthetic control (bigger is the weight, more important is the control unit).

We chose a vector $\mathbf{W}^* = (w_2^*, \dots, w_{J+1}^*)'$ such that the resulting synthetic control best approximates the company exposed to the CDP with respect to the outcome predictors $\mathbf{Z}$, defined in



Source: Author's elaboration.

Figure 4.4: Application of synthetic control method (with $T_O + 1 = 5$)

Sector	Treated	Total controls	Controls per sector
Consumer Discretionary	10	12	(12 CD)
Consumer Staples	12	16	(4 CS, 12 CD)
Industrial	18	18	(18 INDU)
Information Technology and Telecommunication	12	18	(2 ITTE, 3 HC, 9 FINA, 4 CS)
Energy	3	14	(5 ENGY, 3 UTIL, 6 MATR)
Materials	5	11	(6 MATR, 5 ENGY)
Financials	3	9	(9 FINA)
Health Care	7	9	(3 HC, 4 CS, 2 ITTE)
Utilities	3	14	(3 UTIL, 5 ENGY, 6 MATR)

Note: In parenthesis you find the composition of the donor pool per sector.

Source: Author's elaboration.

Table 4.7: Constitution of the donor pools

equation (4.1), and special predictors $Y_j^{K_1}, \ldots, Y_j^{K_M}$, defined in equation (4.2). That is, we want the equations (2.7) be satisfied. As we saw in chapter 2.2.1, the equations (2.7) do not hold exactly, so we select the vector $\mathbf{W}^*$ such that the distance given by equation (2.8) is minimised (the values of the vector and matrix $\mathbf{X}_1$ and $\mathbf{X}_0$ have been defined below).

Note that the vector $\mathbf{W}^*$ is a function of the diagonal matrix $\mathbf{V}$. The matrix $\mathbf{V}$ defines the weights of the company's characteristics in the synthetic control, and so we can consequently get the similitudes between the treated firm and its synthetic control.

In order to estimate the weights in vector $\mathbf{V}$ and by consequence the ones in $\mathbf{W}^*$, we use the data-driven procedure, more specifically the nested optimisation procedure described in section

2.2.2. By this method, we choose $\mathbf{V}^*$ among all positive definite $(k \times k)$[12] diagonal matrix $\mathbf{V}$, in our case $k = 8 + T_0$[13], such that the mean squared prediction error of the outcome variable is minimised over the entire pre-treatment period, that is T_p[14] is equal T_0.

Estimation of the treatment effect

Once the optimal weights of the synthetic control have been estimated by the nested optimisation, we can calculate the estimated treatment effect for each of the treated unit by the following equation:

$$\hat{\alpha}_{1t} = GHG\_EMP_{1t} - \sum_{j=2}^{J+1} w_j^* GHG\_EMP_{jt}, \quad \forall t > T_0. \tag{4.3}$$

Alternative model

In the model selection process we also considered a model with the variable `GHG` (CO2 emissions) as potential outcome variable. We selected $\mathbf{Z}_j = (\overline{R}, \overline{GP}, \overline{COGS}, \overline{EMP}, \overline{KL}, \overline{GHG\_EMP}, \overline{P}, \overline{RI})'$ as the vector of predictors for the unit j and $Y_j^{\mathbf{K}_1}, \ldots, Y_j^{\mathbf{K}_M} = GHG\_EMP_{j1}, \ldots, GHG\_EMP_{jT_0}$ as the vector of special predictors for the unit j. This model had extremely high values of the loss functions that we tried to minimise by the nested optimisation. This effect is coming from the fact that the CO2 emissions are very different between the companies and therefore this heterogeneity does not allow to find a good fit. Though we opted for the model with the variable `GHG_EMP` as the potential outcome variable, given that this variable normalises the emissions and becomes adjusted to the size of the company.

4.3.2 Check of the results

Before applying any statistical tests the first step is to check the results of the analysis. There are two ways to examine the results: visually on the graphs and quantitatively by the tables[15].

First of all, we check the path and gaps plots of the treated unit. Figure 2.4 shows different possible results. But we mainly use the figure 2.5 to analyse if there is a good matching in the pre-treatment period between the treated unit and its synthetic control, and whether there is a treatment effect during the post-treatment period. In order to have a good match, there should be a very small (or even nonexistent) gap between the treated unit and its synthetic control. That is, the gap's line should be as close as possible to the zero gap line during the pre-treatment period. And in order to consider positive treatment effect of the CDP on the CO2 emissions, the treated

[12] k is the number of predictors.

[13] Where 8 is the number of confounders and T_0 is the number of the special predictors. T_0 varies between 4 and 5, depending on the treatment year of the treated company.

[14] T_p is some set of pre-treatment periods over which the RMSPE is minimised.

[15] The presentation of the results of the analysis is explained in details in section 2.2.3.

unit's carbon path should be lower than its synthetic control's carbon path. That is, the gap's line should be decreasing after some initial treatment period $T_0 + 1$. If the gap's line lays close to zero or is even increasing in our case, we consider the results are showing no effect of the CDP.

Once we checked graphically the carbon path, we analyse the quantitative results. More precisely, we built tables analog to tables 2.2 – 2.5 representing some outcomes of the analysis. First, we check the results of the table 2.5 that gives us an idea how well the synthetic control reproduces the values of different companies' characteristics before the treatment and how well it outperforms the averages.

Then we check the relative contribution of each predictor and control units, as explained in tables 2.2 and 2.3, as well as the loss functions values for w and v, that are the mean squared predictors errors defined in the equations (2.8) and (2.9) respectively, which we have minimised by nested optimisation method.

The last step is to analyse the gaps (cf. table 2.4). We want to have the gap close to 0 during the pre-treatment period and negative during the post-treatment period. Moreover we calculate the average treatment effect for the full post-treatment period (equation (2.11) with $\hat{\alpha}_{1t}$ defined in equation (4.3), $t_1 = To + 1$ and $t_2 = T$), which gives us an indication of the size of the treatment effect. But we do not take it as an ultimate indicator, as we also check the path plot and gaps during all periods. Say that it might be that there is a very high negative treatment effect for only one single period, and the rest of the time there is no effect.

Note that if there is no good match between the treated company and its synthetic control, the plots and tables that we use for the results' analysis helps to detect different potential problems. We can identify if there is any kind of influence of just one year or one control unit and where the problem is. In some cases just to take one variable or one observation out helps already to get more satisfying results.

4.3.3 Applied tests

By using the synthetic control method, we can test the results of the analysis. In our case, we tested the treatment effect by using one of the falsification test so-called "in-space placebo". We also examined the misspecification of the model by using the root mean squared prediction error and its related indicators. Finally, we applied robustness tests in order to check the quality of our model with respect to the number of variables and observations in the donor pool. The application of these methods is explained in this section, but for more detailed information about statistical inferences applied in the case of the synthetic control method see the chapter 2.3.

In-space placebo

The main idea of placebo studies is to predict the counterfactual outcome path for the companies in the donor pool, knowing that the units that do not receive the treatment should not be affected by it[16]. As already mentioned, in our case we do use the "in-space placebo" test, where we apply the synthetic control method to every potential control company in the respective sample.

For each of "placebo-treated" company we calculate the treatment effects, the gaps and construct the placebo effect graphs (see the figure 2.7) which helps us to analyse the significant evidence of a treatment effect for the treated unit. Ideally, we would like to get for each treated unit the results similar to the one on the graph 2.7a. That is, negative values of the gaps for the treated unit and as a consequence, its gaps' line laying below the "placebo-treated" units' gaps lines.

Additionally, we use the placebo effect graph to calculate a specific pseudo p-value (see definition 2.1) by using the equation (2.12), where the number of bad estimates is the number of lines laying above the treated unit's gaps line and the total number of units is the number of lines. Note that the number of the tested units might be different to the number of the units in the specific sample as we have excluded observations with respect to the certain threshold of the RMSPE from the placebo test donor pool (see the next section).

Root mean squared prediction error

Moreover, we calculated for each unit in the sample the root mean squared prediction error, which is another measure to evaluate the treatment effect[17].

More precisely we calculated the pre-treatment and the post-treatment RMSPE using the formula (2.13), where the number of periods varies between 4 and 5 depending on which is the year the treated company started to participate to the CDP. The values of t_1 and t_2 are equal to 1 and T_0 for the pre-treatment RMSPE, then T_0+1 and T for the post-treatment RMSPE. The value of k (treated unit) varies with respect to the company that we calculate the RMSPE for.

With the pre-treatment and post-treatment RMSPE, we get for each unit in the sample the RMSPE-ratio defined in the equation (2.14). And we obtain consequently the RMSPE-ratio p-value defined in the equation (2.15), where the number of RMSPE-ratio bad estimations is the number of companies that did not participate to the CDP and have larger RMSPE-ratio than the one that participates to the program. In order to interpret the values of the RMSPE and its associated indicators we use the table 2.7.

As already mentioned before, for the in-space placebo test we construct four different placebo effect graphs. The first one excludes all the companies having the RMSPE hundred times larger than the treated company. The second one uses twenty times rule, the third one five times rule and the last one excludes the control companies having the RMSPE two times larger than the company participating to the CDP. An example of the four graphs is represented by the figure A.12 in the annexe. For each graph, we get a pseudo p-value and then we do the average pseudo p-value for the four graphs. It is another control p-value, but as the main pseudo p-value, we use the five times rules.

[16] For more information about the placebo tests see section 2.3.1.
[17] For more information about the RMSPE see section 2.3.2.

Robustness tests

In order to set the robustness of our model we used the sensitivity analysis of the number of controls and the number of variables, both described in section 2.3.3. We conclude that adding different variables to the model does not improve the estimations and the v loss function remains constant. Though, the selected variables have a good predictive power already. Also, in general, having a large number of control units will apriori increase the quality of the estimation and the likelihood to get a perfectly fitting synthetic control. But on the other side, once the synthetic control is estimated, decreasing the number of the control units in the donor pool does not necessarily decrease the quality of the estimation, that is, the w loss function reminds more or less the same. We did not carry any other robustness tests.

4.3.4 Justification of the choice of the variables

Table 4.8 shows results that confirm the choice of the predictors. We found positive and significant relations between CO2 emissions (GHG) and revenue, cost of goods sold, share price and capital-labour ratio. The first two results suggest that a bigger firm usually has higher emissions. The positive relation between CO2 emissions and share price seems unexpected, as we would anticipate that the market would punish firms with increasing emissions. This result could be due to the strong positive correlation that we found between share price and revenue. And as the market reflects the financial result immediately to the share price, this relation could be potentially stronger that the one with the emissions. Furthermore, the positive relationship of CO2 emissions with the capital-labour ratio advocate that the firms that are heavily dependent on machinery and equipment tend to be more polluting than those that are labour intensive.

Predictors	GHG	GHG_EMP
R	0.18^{****}	0.62^{****}
COGS	0.17^{****}	0.14^{****}
EMP	0.25^{****}	-0.12^{****}
P	0.65^{****}	0.24
RI	-0.01	-0.01
KL	0.19^{****}	0.06^{*}

Note: non significant $p > 0.05$, $*p \leq 0.05$, $****p \leq 0.0001$

Source: Author's elaboration.

Table 4.8: Correlations and significance of the correlations

Still, based on table 4.8, a negative correlation was found between CO2 emissions and return on investment. This result was expected, but not significant. The number of employees showed a positive correlation with the CO2 emissions. Again, this approves the theory that emissions are generally growing with the size of the firm. Although we found that large firms try to be less pollution-intensive than smaller firms, which can be associated with the economics of scale. That is, we detect a negative and significant relationship between a number of employees and CO2 emissions per employee (GHG_EMP), and the relationship was even more evident in each sector. Our results support most of the previous research that we presented in the brief literature review of firms' environmental evaluation in the section 4.1.1.

4.4 Application in R

For the construction of the panel database, the computation of the descriptive statistics, the determination of the pertinent variables and the adjustment of the model, we used the statistic program R (R Core Team (2013)). More precisely we applied the libraries Hmisc (Harrell et al. (2016)), gmodels (Warnes et al. (2015)), vcd (Meyer et al. (2016)), reshape (Wickham (2007)), and gdata (Warnes et al. (2015)). In this section, we will not describe the cited packages or their associated functions, but we concentrate on the library "Synth", the R package developed by Hainmueller and Diamond (2015) for synthetic control methods in comparative case studies. Moreover, we present the library "Mylib", a package we built, that contains different functions created in order to adapt the package "Synth" on our case. We also present the "Jobs" that produce the synthetic control analysis. Furthermore, in order to help the presentation of the results of our study in chapter 5 we also show the outcomes of the most important functions in the annexe A.4 by using an example of one company from the consumer discretionary sector.

4.4.1 Package "Synth"

The package "Synth": "Synthetic Control Group Method for Comparative Case Studies" implements the synthetic control group method for comparative case studies as described in Abadie and Gardeazabal (2003); Abadie et al. (2010, 2011, 2015). For a better understanding, there is a manual by Abadie et al. (2011), that uses the example that takes example of the terrorist conflict in the Basque Country as a study case (see Abadie and Gardeazabal (2003)). This article shows how to run the library "Synth" and shows the concrete implementations of different functions and the results of the analysis. Therefore for a better understanding of the implementation of the SCM, we are referencing the reader to this article.

The five most important functions of the package and their descriptions are presented in the table 4.9. The application of these functions in our study (construction of the "Job") is shown in the figure 4.5, where the functions from the "Synth" package are in red boxes.

An example of outcome of the function synth() is presented in the annexe on the figure A.3. The values are the estimate of the loss function from the nested optimisation (functions (2.8) and (2.9)), the weights of the vectors $\mathbf{V}^*$ and $\mathbf{W}^*$. Moreover, examples of the gaps.plot() and path.plots() outcomes are shown on the figure 2.4. Further, examples of the outcome of the synth.tab() are shown on the figures A.5 – A.7 in annexe, which represents a concrete numerical view of the tables 2.2, 2.3, 2.5 respectively.

Synth	
dataprep()	Constructs a list of matrices from panel dataset to be loaded into the function synth(). The output of the function dataprep() contains a list of matrices. In order to run the function we need the following arguments: data frame with the panel data (wdf), predictors (pr), operators that act upon these predictors – eg. "mean" (pr.op), dependent variable (pr.op), unit variable numbers (u.v), time periods (t.v), unit names variable (u.n.v), time-period over which outcome data should be plotted (t.p), treated unit (tr.id), control units (cd.id), special predictors (sp.pr), the time-period over which to select the predictors (t.pr.p), time-period over which to optimise (t.op.ssr);
gaps.plot()	Plots gap in outcome trajectories between the treated and its synthetic control unit. This function plots the gaps in the trajectories of the outcome variable for the treated unit and the synthetic control group constructed by synth() and dataprep(). The user can specify whether the whole time period or only the pre-treatment period should be plotted;
path.plot()	Plots outcome trajectories between the treated and its synthetic control unit. This function plots the trajectories of the outcome variable for the treated unit and the synthetic control group constructed by synth() and dataprep(). The user can specify whether the whole time period or only the pretreatment period should be plotted;
synth()	Constructs synthetic control units for comparative case studies. synth() estimates the effect of an intervention by comparing the evolution of an aggregate outcome for a unit affected by the intervention to the evolution of the same aggregate outcome for a synthetic control group. synth() constructs this synthetic control group by searching for a weighted combination of control units chosen to approximate the unit affected by the intervention in terms of characteristics that are predictive of the outcome. The evolution of the outcome for the resulting synthetic control group is an estimate of the counterfactual of what would have been observed for the affected unit in the absence of the intervention;
synth.tab()	Creates tables that summarise results of synthetic control group method. This function is called after dataprep() and synth() in order to create tables summarising the results of the run of the synthetic control method.
Mylib	
sp.pr.f	Creates a list of the special predictors to be used in the function dataprep();
year.vec.f	Creates a vector that defines the time vector that is specific to the treatment variable with respect to the treatment year;
unit.par.f	Gives the values of the parameters for the unit of interest;
dataprep.arg	Creates a list of arguments to be used in the function dataprep();
gaps.f	Calculates the gaps of the output variable between the treated unit and its synthetic control;
path.plot.f	Gives summary "path" plots;
gaps.plot.f	Gives summary "gaps" plots;
p.vec.par.f	Gives the vector of values of the parameters for the unit of interest, which will be used in the placebo tests;
placebo.data.f	Produce the placebo data, as the placebo gaps, synth.tables(), daparep() values and synth() outputs;
mse.f	Creates a list of different mean squared prediction errors, root mean squared errors and associated ratios;
p.synth.plot.f	Gives summary gaps plot, that represents the "true" treated unit and the "placebo" (control) treated units.

Table 4.9: Functions in the package "Synth" and library "Mylib"

4.4.2 "Mylib"

The library "Mylib" prepares the data to be used by certain functions in package "Synth", but also contains new functions that calculate important elements in the synthetic control analysis. The package "Mylib" is presented in the annexe B.1. Each of the eleven functions is briefly described in the table 4.9 (for more details see the annexe B.1). In the figure 4.5 we describe the combination and interactions between the library "Mylib" and the package "Synth". It shows, in particular, the structure of the different "Jobs" we constructed. The function of the "Mylib" is in the green boxes.

Indeed, there are five main functions: gaps.f(), gaps.plot.f(), path.plot.f(), g.gaps.data.f(), and mse.f(). We provide for the interested reader in annexe A.4 a reflective example which gives the output of our functions.

An example of the outcome of the function gaps.f() is presented in the annexe on the figure A.4. The gaps represent the treatment effect for each of the year, respectively the difference between the treated company's CO_2 emissions per employee and the values of the same outcome variable of its synthetic control. Moreover, examples of the gaps.plot.f() and path.plot.f() functions' outcomes are shown in the annexe on the figure A.8. Further, the example of the placebo gaps, as one of the values of the p.gaps.data.f() function, is shown in the annexe on the figure A.9, where we have the gaps of each "placebo-treated" companies. Figure A.10 in annexe represents outcomes of the function mse.f(). And finally, the figure A.11 in annexe shows an example of the placebo effect plots, as already presented theoretically on the figure 2.7.

4.4.3 Workflow implementation

For each of the sectors, we programmed a specific "Job" in order to execute the synthetic control analysis, test and prepare the results to be evaluated and compared. The "Job" uses the packages "Synth" and "Mylib" that we have presented in the previous sections. Each of the jobs performs analysis for the individual company from the specific sector. One of the jobs of the consumer discretionary sector, more specifically for the company "DEBREHAM PLC", is presented in the annexe B.2.

Moreover, detail explanations of the five important steps in the "Job" are explained in following paragraphs. These correspond to the bullets in the figure 4.5. Concerning the figure, note that the red boxes contain functions from the package "Synth" and the green boxes the ones from the package "Mylib". If the function is used by another function or to create another argument, it is also represented in the box (e.g., t.pr.p and *sp.pr.f() respectively). The black box contains the arguments to be used in the function dataprep.arg().

The steps are the following:

1. Define general and specific values of the arguments to be used in the function dataprep.arg() and consequently in dataprep(). The arguments are briefly described in the table 4.9 in the dataprep() description. In this step and with respect to the methodology, we describe all the main elements of the model (see section 4.3.1).

2. Run the dataprep.arg() and dataprep() functions in order to prepare the list of objects necessary for running function synth() and the other functions of the package "Synth" to construct synthetic control groups.

3. Run the synth() function, which is the synthetic control command to identify the optimal weights of the synthetic control. In this step, we are estimating the optimal weights as described in the section 4.3.1.

4. Compute the gaps (estimation of the treatment effect as described in the section 4.3.1), the treatment effects for each of the periods, and summarise the results in the tables, print out the path and gaps plots. In this step, we use the functions gaps.f(), synth.tab(), path.plot.f() and gaps.plot() respectively. This part is corresponding to the section 4.3.2.

5. Execute the placebo test, as explained in the section 4.3.2, in the three following steps:

   - Define the vector of the id's and names for the placebo-treated units via function p.vec.-par.f();
   - Produce the placebo data. That means that we run the synthetic control estimation via function synth() for each of the "placebo-treated" companies. This step is managed by the function placebo.data.f();
   - Compute the gaps for each of the "placebo-treated" companies, which is just one of the values of the function placebo.data.f(), more precisely the value p.gaps.data. The example of the output is given in the figure A.9 in the annexe.
   - Calculate the root mean squared prediction error and related statistics for each unit in the sample by using the function mse.f(). An example of the output is in the figure A.10 in the annexe.
   - Produce the placebo gaps plot by using function p.synth.plot.f(). An example of the output is in the figure A.11 in the annexe. Note that we exclude all the observations having the mean squared prediction error higher than five times the mean squared prediction error of the treated unit and with these observations.

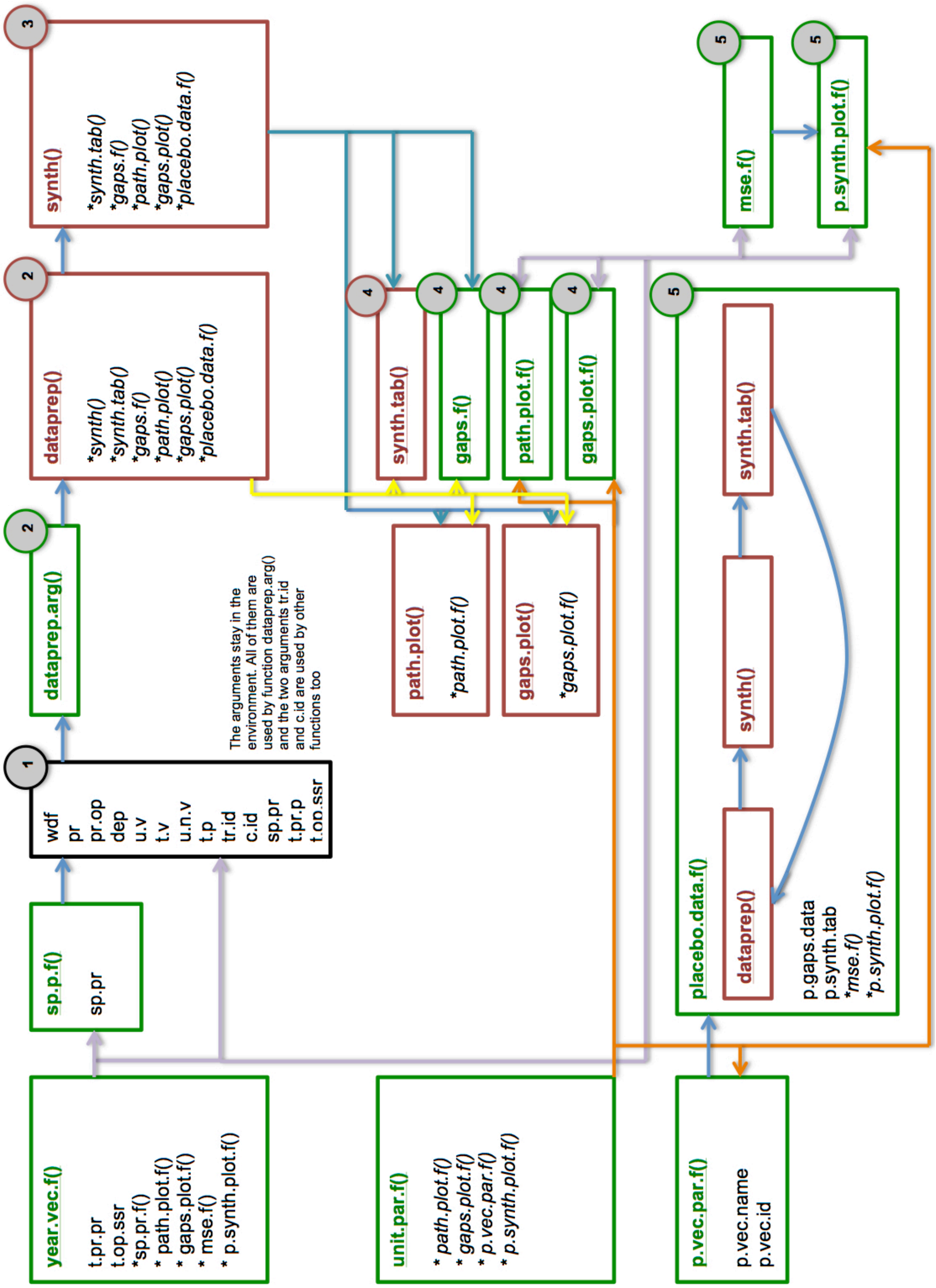


Figure 4.5: Functions interactions in R and steps in the job

Chapter 5

Estimations and results

In the previous chapter, we set up the objective of our study, which is to evaluate the impact of the Carbon Disclosure Project CDP on the firm's greenhouse gas emissions. Moreover, we want to compare the results of the assessment on international and sectoral levels. The three research questions, that we already mentioned in the table 4.1 are the following.

The first one is: *"Is there a positive impact of the Carbon Disclosure Project on the participating firms?"* The second one is: *"Is there a difference in the impact on the international level, between European Union, United Kingdom, United States?"* And the last one is: *"Is there a difference in the impact between the sectors of activities?"*

To answer these questions we used the synthetic control analysis covered in chapter 2. All the details about data, including the descriptive statistics, the model and its implementation, and the used tests, are covered in chapter 4. In this chapter, we present the results of our analysis and answer the three research questions.

As we already discussed before, our data contains 73 treated companies, divided into 3 geographic regions[1] and 9 sectors[2]. In the first section of this chapter, we present the overall analysis results regardless the sector or geographic region. In the second section, we detail the results of the analysis by region. We also give an example of the interpretation of the results from the three regions for the companies that are part of the information technology and telecommunication sector. More precisely we interpret the results for the companies having a decline in the CO2 emissions per employee after starting to report to the CDP. We will be able to note if there is no treatment effect, a small not significant treatment effect, significant treatment effect, and a highly significant treatment effect. In the third section, we depict the results by sector. First, we analyse and compare the results in different emitter groups: the light emitters, the middle carbon emitters, and the heavy emitters. Then we present more detailed analysis in each sector. And finally, in the last section, we terminate the chapter by a short conclusion on the three research questions. Note that the statistical inferences results are presented in table 5.4 and the annexe A.5, where we show the figures of the path and placebo plots for all the treated companies with a positive treatment effect.

[1] The regions are: EU, UK, US.

[2] The sectors are: CD, CS, INDU, FINA, HC, ITTE, ENGY, MATR, UTIL.

5.1 General results

In this section we review the results of the analysis without taking into account the sector or region the company is a part of. In order to evaluate for each company the effect of the Carbon Disclosure Project on the carbon emissions, we have calculated the following statistics: treatment effect[3], average treatment effect[4], pre-treatment root mean squared prediction error (RMSPE)[5], RMSPE-ratio[6]. Moreover we constructed individual path and gaps plots[7] for each company and applied the in-space placebo test which allowed us not only to calculate the RMSPE-ratio p-value[8], but also to construct the placebo effect graph[9] and estimate the placebo p-value[10].

Table 5.1 gives the summary results of the analysis for all companies regardless the sector or geographic location. In total, out of the 73 companies that participate in the Carbon Disclosure Project, we have observed 6 treated companies with extremely large CO2 emissions per employee (large values were also detected for other predictor variables). Their pre-treatment RMSPE was higher than 200. This very large pre-treatment RMSPE indicates a problem of extreme value observations, and so there was no combination of units in the sample that could reproduce the time series of the potential outcome prior the treatment. Thus, we did not find any matching synthetic control for them, and the six firms were removed from our analysis.

The rest of the companies performed well, and their pre-treatment RMSPE was lower than 10. This relatively low pre-treatment RMSPE shows good matching results between the treated firm and its synthetic control. Out of the remaining 67 companies, 48 companies revealed decrease of CO2 emissions per employee after signing to the CDP. That is, we observe negative values of the treatment effect for most of the post-treatment periods, and the average treatment effect was lower than zero. This result would suggest a 72% success rate of the program before the test.

Number of companies	
73	
-6	Extreme
67	Treated
-19	No effect
48	Decline in CO2
(72%)	Success in decrease of CO2 per employee

Source: Author's elaboration.

Table 5.1: Summary results

Table 5.3 presents overall results after the tests, and table 5.4 shows detailed inference test results for all companies with a positive average treatment effect. In order to decide on the degree

[3] Defined in equation (4.3).
[4] Defined in equation (2.11) with $\hat{\alpha}_{1t}$ defined in equation (4.3), $t_1 = To + 1$ and $t_2 = T$.
[5] Defined in equation (2.13) with t_1 and t_2 are equal to 1 and T_0.
[6] Defined in equation (2.14).
[7] See annex A.5.
[8] Defined in equation (2.15).
[9] See annex A.5.
[10] Defined in equation (2.12).

of the pertinence of the average treatment effect, we based ourself on the value of the treatment effect, the pre-treatment RMSPE, the RMSPE-ratio, the RMSPE-ratio p-value, and the pseudo p-value. In table 5.2 we summarise the threshold values of the mentioned statistics, which categorise the treatment effects in four degrees of significance, that is: no treatment effect, small not significant treatment effect, low significant treatment effect, and highly significant effect. The threshold values were based on a subjective decision with respect to our case.

Sign		Average treatment effect	RMSPE	RMSPE-ratio	RMSPE-ratio p-value	Placebo p-value
(-)	No treatment effect	< 0	< 10	< 1.1	x	x
(+)	Small treatment effect but not significant	< 0	< 10	> 1.1	x	> 0.4
(*)	Low significant treatment effect	< 0	< 10	> 1.1	x	< 0.4
(**)	Highly significant treatment effect	< 0	< 10	> 10	< 0.2	< 0.3

Source: Author's elaboration.

Table 5.2: Treatment effect signs' explications

As presented in the table 5.3, out of the 48 companies with evident decline in CO2 emissions per employee, 10 have RMSPE-ratios lower than 1.1. This means that their CO2 emissions per employee were no different from before the company signed to the CDP. Thus for these companies, we cannot approve the improvement in carbon performance despite the decrease in emissions during the post-treatment period. This result leaves us with 38 companies showing a positive change in the post-treatment period.

Out of the 38 companies, about 77% have relatively small pseudo p-value, which indicates a significant improvement from the pre-treatment period. The remaining 7 companies are considered as having the not significant treatment effect. The rest of the 21 companies have relatively small RMSPE-ratios and are characterised with high RMSPE-ratios p-values indicating no significant improvement from the pre-treatment period with respect to the other placebo-treated companies. For these 21 companies we could not approve with placebo tests and RMSPE-ratios a significant and positive treatment effect, so we classify them as “low significant”. On the other side, 10 companies outperform the other ones in the values of the tests. They all have relatively high RMSPE-ratio with respect to the rest of the firms. This high ratio shows a large decrease in CO2 emissions per employee. The results are supported by both low placebo and RMSPE p-values for all ten companies, showing that other placebo-treated companies did not perform as well as the treated companies under investigation.

Total	48	companies with decrease in CO2 emissions per employee
$(-)$	10	without significant change with respect to pre-treatment period
$(+)$	7	with at least 10% decrease of CO2 with respect to the pre-treatment period
$(*)$	21	with at least 10% decrease of CO2 with respect to the pre-treatment period and significant placebo test results
$(**)$	10	with at least 100% decrease of CO2 with respect to the pre-treatment period, and highly significant placebo test and RMSPE test results

Source: Author's elaboration.

Table 5.3: Summary of significant treatment effects

Region	Sector	Name	Tr.effect	RMSPE	RMSPE-ratio	RMSPE-ratio p-value	Placebo p-value
European Union	CD	Gtech Spa	-0.41^{-}	0.73	0.83	1.00	0.43
	CD	Nokian Renkaat	-2.88^{**}	0.49	6.24	0.23	0.08
	CD	Valeo Sa	-2.10^{*}	0.25	3.77	0.54	0.23
	CS	Greencore Group	-6.14^{*}	2.57	2.65	0.64	0.09
	CS	Jeronimo Martins	-0.56^{+}	0.10	4.77	0.41	0.55
	CS	Koninklijke Phil	-2.85^{*}	2.44	1.44	0.82	0.08
	INDU	Atlantia Spa	-4.18^{**}	0.45	11.59	0.26	0.07
	INDU	Centrotec Sustai	-0.76^{-}	2.97	0.25	1.00	0.31
	INDU	DCC Plc	-1.07^{+}	0.37	4.75	0.47	0.81
	INDU	Flsmidth Co	-2.13^{*}	1.24	1.77	0.79	0.11
	INDU	Kobenhavns Lufth	-3.59^{*}	1.62	2.22	0.47	0.05
	INDU	Kone Oyjb	-1.09^{*}	0.04	2.30	0.74	0.36
	INDU	Obrascon Huarte	-3.72^{**}	0.33	14.57	0.21	0.06
	HC	William Demant	-2.29^{*}	1.09	2.10	0.60	0.20
	ITTE	Dassault System	-0.82^{*}	0.14	6.55	0.21	0.38
	ITTE	Seagate Technolo	-8.18^{*}	1.22	7.96	0.42	0.09
	ITTE	Vaisala Oyja Sh	-1.09^{+}	0.56	2.45	0.78	0.45
	FINA	Banco Com Portr	-0.43^{+}	0.41	1.24	0.70	0.54
	FINA	Generali Assic	-0.34^{-}	0.56	0.88	0.90	0.54
	ENGY	Saipem Spa	-0.14^{+}	0.02	9.35	0.57	0.57
	UTIL	Enagas Sa	-0.41^{-}	0.66	1.10	1.00	0.45
United Kingdom	CD	Debenhams Plc	-0.72^{*}	0.16	5.47	0.46	0.28
	CD	Dignity Plc	-0.62^{-}	0.36	0.61	0.62	0.52
	CS	Mcbride Plc	-4.47^{**}	0.03	23.03	0.11	0.15
	INDU	Serco Group	-1.57^{**}	0.08	19.19	0.10	0.18
	HC	BTG Plc	-12.43^{*}	9.57	1.30	0.50	0.11
	HC	Synergy Health	-3.28^{*}	2.21	2.34	0.40	0.12
	ITTE	Computacenter Pl	-0.39^{-}	0.38	1.06	0.92	0.77
	ITTE	Pace Plc	-1.15^{+}	1.15	1.33	0.78	0.67
	FINA	Savills Plc	-1.66^{-}	4.25	0.80	0.90	0.54
United States	CD	Leggett & Platt	-14.15^{*}	8.53	1.84	0.84	0.08
	CD	Lowe's Cos Inc	-0.93^{-}	3.24	1.06	1.00	0.41
	CD	Vf Corp	-0.68^{-}	0.87	1.04	0.92	0.36
	CS	Constellationa	-4.87^{**}	0.62	14.13	0.18	0.07
	CS	Estee Lauder	-0.61^{**}	0.14	15.71	0.06	0.35
	CS	Hershey CO	-7.32^{*}	4.87	1.61	0.82	0.06
	CS	Philip Morris	-4.12^{*}	1.73	2.41	0.64	0.15
	INDU	ABM Industries	-0.24^{*}	0.05	6.67	0.11	0.50
	HC	Actavis Plc	-2.53^{**}	0.19	14.87	0.10	0.16
	HC	Celgene Corp	-4.16^{**}	0.36	12.26	0.20	0.17
	ITTE	Akamai Technolog	-9.17^{*}	5.56	2.18	0.56	0.07
	ITTE	Broadcom Corpa	-1.02^{*}	0.02	8.95	0.47	0.23
	ITTE	Cognizant Techa	-1.95^{*}	0.23	8.48	0.60	0.10
	ITTE	Microchip Tech	-17.25^{**}	0.45	50.18	0.14	0.13
	ITTE	Western Digital	-1.15^{*}	1.00	1.97	0.83	0.17
	MATR	Cliffs Natural R	-6.05^{-}	1.02	0.76	0.50	0.36
	ENGY	Noble Energy Inc	-6.16^{*}	0.98	6.83	0.50	0.08
	UTIL	Quest Diagnostic	-0.02^{+}	0.02	2.24	0.57	0.50

Source: Author's elaboration.

Table 5.4: Placebo tests results

5.2 Results by region

In this section, we analyse the results with respect to the regions the companies are from. Table 5.5 shows the summary results distributed by region. Once the extreme values are removed, the data contain 28 observations from the European Union, 14 from the United Kingdom and 25 from the United States. There is no effect for 7 firms from EU, 5 firms from UK, and 7 firms from US, which gives about a 70% success rate in decrease of CO_2 emissions per employee. The highest rate is 75% for EU, 72% for US, and 64% for UK. As we can observe, the success rate decreases with the number of firms in the respective samples. Thus, before the placebo test, we can not conclude that one region performs better than the other in term of the success of the Carbon Disclosure Project.

EU	UK	US	
29	16	28	
−1	−2	−3	Extreme
28	14	25	Treated
−7	−5	−7	No effect
21	9	18	Decline in CO_2
(75%)	(64%)	(72%)	Success in decrease of CO_2 per employee

Source: Author's elaboration.

Table 5.5: Summary results by region

The table 5.4 presents the results of the placebo tests per company and region. The summary of significant treatment effects by region is presented in the table 5.6. We remark that for the European Union there is a 14% of the companies without significant change after the CDP comes into force, for the United Kingdom it is 19%, and for the United States 16% of companies. Taking into account only the companies with significant change with respect to the pre-treatment period[11], the analysis reveals it for 57% of companies from EU, 31% from UK, and 83% from US. The remaining 7 companies from the three regions show a low decrease in the CO_2 emissions per employee but is considered as not significant.

So far we can say that the United States indicate better performance. This is also proven by the ratio of the companies that outperform the other ones in the values of the tests. Meaning that they have a large decrease in CO_2 emissions per employee (relatively high RMSPE-ratio, and low placebo and RMSPE p-values, with respect to the rest of the firms). These companies are classified as highly significant and 27% of the US companies are concerned, versus 14% of EU and 13% of UK companies. Note, that if UK would have been considered in EU region, the CDP would have the same success. But as it is not, we consider the United States as a slightly outperforming region.

5.2.1 Interpretation of companies from different regions from information technology and telecommunication sector

The figure 5.1 presents the path plot and the synthetic matching and permutation tests for four companies from information technology and telecommunication sector. These companies are *Microchip Tech*, *Seagate Technolo*, *Pace Plc*, *Computacenter Pl*, and they are from US, EU, and last

[11]The significant improvement from the pre-treatment period is indicated by a relatively small pseudo p-value,

	EU	UK	US	
Total	21	9	18	companies with decrease in CO2 emissions per employee
(−)	4	3	3	without significant change with respect to pre-treatment period
(+)	5	1	1	with at least 10% decrease of CO2 with respect to the pre-treatment period
(∗)	9	3	9	with at least 10% decrease of CO2 with respect to the pre-treatment period and significant placebo test results
(∗∗)	3	2	5	with at least 100% decrease of CO2 with respect to the pre-treatment period, and highly significant placebo test and RMSPE test results

Source: Author's elaboration.

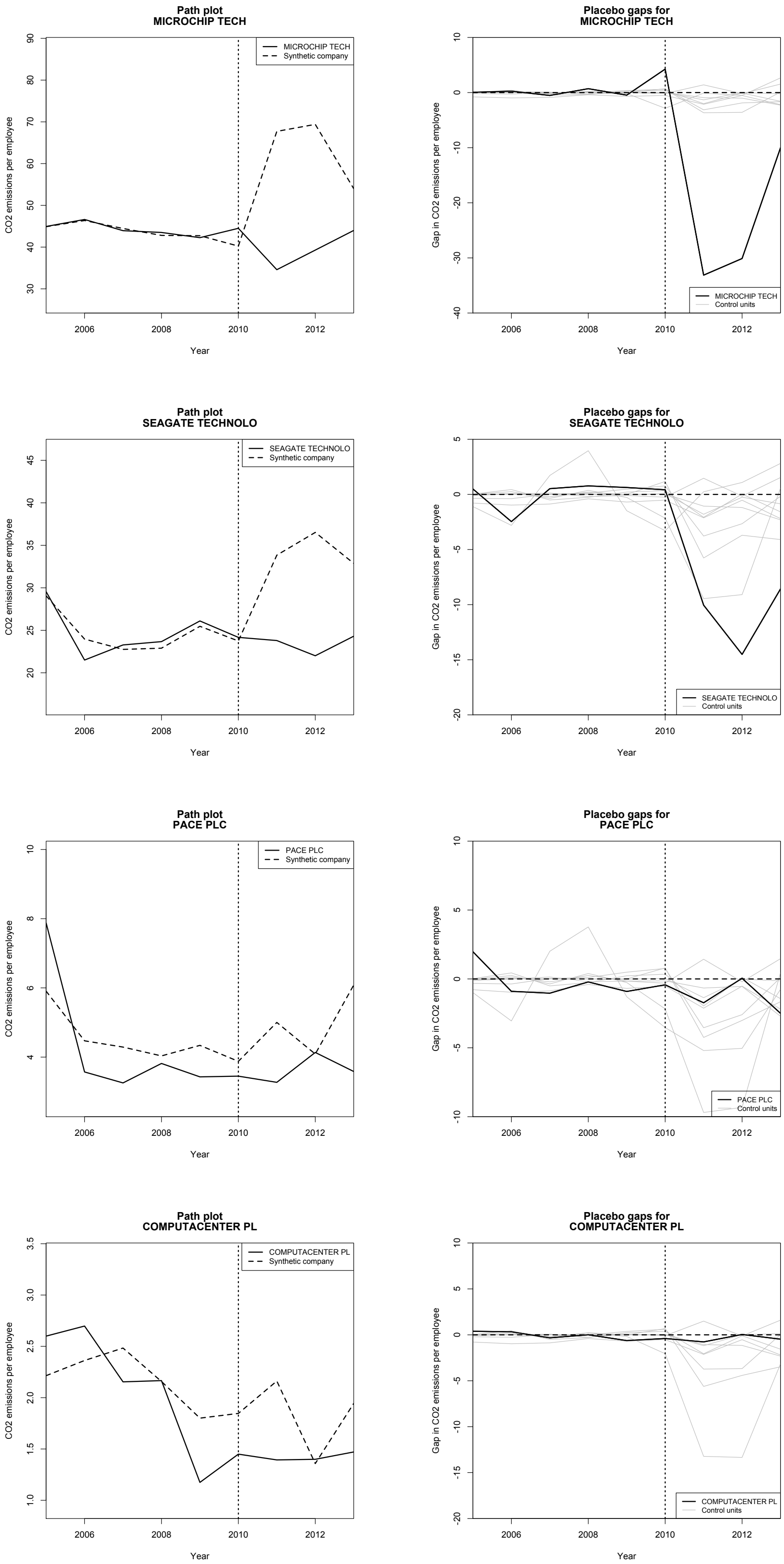
Table 5.6: Summary of significant treatment effects by region

two from UK respectively. Note, that the same tables for the rest of the companies from the three regions are presented in the annexe A.5 (figures A.13 – A.24), and can be interpreted in the same way. More precisely, the first graph is showing a company with highly significant treatment effect, the second line is for a firm with low significant treatment effect, the third company represents small but not significant treatment effect, and the last line is for a firm with no treatment effect.

The first column of figure 5.1 shows the graphs of the gaps of the CO2 emissions per employee for four treated companies and their synthetic controls. The almost parallel lines in pre-treatment period (before the vertical line), for *Microchip Tech* and *Computacenter Pl*, indicate a good match between the treated company and its synthetic control with respect to the CO2 emissions per employee. This result is approved by small pre-treatment RMSPE. *Pace Plc* and *Computacenter Pl* has a relatively bigger gap, which is also reflected in relatively higher RMSPE. Note that the scale of the CO2 emissions per employee is different for the four companies, which can also visually influence the perception. But in all ways, the match is relatively good for the four companies.

The gap between the treated and synthetic control in post-treatment period indicates treatment effect: the bigger the gap, the larger the effect. We observe positive treatment effects, supported by high RMSPE-ratios, indicating large decreases in CO2 emissions per employee in the post-treatment period, for the first two companies. Moreover, we detect quite small RMSPE-ratios for the third and fourth companies.

The second column of figure 5.1 shows the treated units and their relative placebo-treated units. For the first two companies, we can see all placebo-treated units sitting above the treated units under investigation. This means that the positive treatment effect of the treated unit is not random. The results for the first two companies are approved by low placebo and RMSPE p-values, this means that rest of the placebo-treated companies did not do as well as the treated companies under investigation. We could almost consider the second company as a highly significant, as the pseudo p-value is very small, but the RMSPE-ratio p-value is above the threshold. The last two companies have relatively low RMSPE-ratios and high p-values, which approve the not significant results.



Source: Author's elaboration.

Figure 5.1: Synthetic matching and permutation tests for companies from information technology and telecommunications' sector and from United States, European Union, and two from United Kingdom respectively

5.3 Results by sector

In this section we present the analysis with respect to the sectors, which are: financials (FINA), health care (HC), information technology and telecommunication (ITTE), consumer discretionary (CD), consumer staples (CS), industrials (INDU), energy (ENGY), materials (MATR), utilities (UTIL). All the sectors have a different number of companies in the sample, which might bring an obstacle in the interpretation of the results. We first analyse the three groups of sectors, as explained below, and then we take each sector individually and give more details.

5.3.1 Analysis by group of emitters

As already mentioned in the previous chapter, in order to make the comparison between the sectors more plausible, we divide them into three big groups: light, medium, and large carbon dioxide emitters. The first group, the light emitters, contains the financial, the health care, and the information technology and telecommunication sectors. The group of medium CO_2 emitters contains the consumer discretionary, the consumer staples, and the industrial sectors. And the last group, the heavy emitters, contains the energy, the material, and the utility sectors.

First of all, we analyse the summary results by sector before the tests which are presented in the table 5.7. Individually, the success in the decline of the CO_2 emissions varies between 20 to 100%. But as already mentioned, each sector contains different numbers of observations, and each group as well. After exclusion of the extreme values, the light emitters contains 21 companies, the middle emitters, which are the biggest group, comprise 35 companies, and the big emitters group contains 11 firms only. Success in the decrease of CO_2 per employee is the highest for the light emitters, being equal to 87% of companies achieving the decline in emissions. On the second range is the middle emitters group with 74% of success in the decrease. And finally the last group, with 51% success, belongs to the heavy emitters. So far, before the tests, the light emitters seems to outperform the other sectors.

Light emitters			Medium emitters			Heavy emitters			
FINA	HC	ITTE	CD	CS	INDU	ENGY	MATR	UTIL	
3	7	12	10	12	18	3	5	3	
0	0	-1	-1	-1	-3	0	0	0	Extreme
3	7	11	9	11	15	3	5	3	Treated
0	-2	-1	-1	-3	-6	-1	-4	-1	No effect
3	5	10	8	8	9	2	1	2	Decline in CO_2
(100%)	(71%)	(91%)	(89%)	(73%)	(60%)	(67%)	(20%)	(67%)	Success in decrease of CO_2 per employee

Source: Author's elaboration.

Table 5.7: Summary results by sector

The significant treatment effects by sector are presented in the table 5.8, which is a summary of the placebo tests per company presented in table 5.4. Within the three groups the light emitters contain 25% of companies without significant change after the CDP comes into force, for the medium emitters it is 20%, and for the heavy emitters 33% of companies.

Taking into account only the companies with a significant change with respect to the pre-treatment period, significant treatment effect shows 73% of companies from the low emitters sector, 90% from the middle emitters, and only 25% from high emitters sector. The remaining 9 companies show a low decrease in the CO2 emissions per employee but is considered as not significant.

So far, the light and middle emitters indicate quite a good performance, with slightly better results for the middle-class emitters. Heavy emitters show very poor performance. That is, this last group proves low significant treatment effects for only one out of 11 treated companies. At the end, the highly significant treatment effect, with a large decrease in CO2 emissions per employee (relatively high RMSPE-ratio, and low placebo and RMSPE p-values, with respect to the rest of the firms), concerns 28% of the middle emitters and 16% of light emitters. Thus, the middle emitters group proves to be having slightly better performance.

	Light emitters			Medium emitters			Heavy emitters			
	FINA	HC	ITTE	CD	CS	INDU	ENGY	MATR	UTIL	
Total	3	5	10	8	8	9	2	1	2	companies with decrease in CO2 emissions per employee
(−)	2	0	1	4	0	1	0	1	1	without significant change with respect to pre-treatment period
(+)	1	0	2	0	1	1	1	0	1	with at least 10% decrease of CO2 with respect to the pre-treatment period
(∗)	0	3	6	3	4	4	1	0	0	with at least 10% decrease of CO2 with respect to the pre-treatment period and significant placebo test results
(∗∗)	0	2	1	1	3	3	0	0	0	with at least 100% decrease of CO2 with respect to the pre-treatment period, and highly significant placebo test and RMSPE test results

Source: Author's elaboration.

Table 5.8: Summary of significant treatment effects by sector

5.3.2 Low carbon dioxide emitters

The first group of the three sectors with low carbon emissions that we are going to examine contains the ITTE, the HC, and the FINA sectors. Theses sectors are characterised by relatively low emissions and quite small values of the loss functions and RMSPE-ratios. The following section presents closer analysis of each firm.

Information Technology and Telecommunication sector

Information Technology and Telecommunication sector include 12 treated and 18 controls units. We observed one extremely large treated company with the pre-intervention RMSPE equal to 30, which is much higher than the rest of the companies from the same sector. The company with the extreme values was not considered for further analysis. The rest of the companies performed relatively well and their pre-intervention RMSPE's were lower than 6, with the majority of them having the pre-intervention RMSPE lower than 1. Out of the remaining 11 companies, 10 companies show decrease of CO_2 emissions per employee over the post-intervention period. And our statistical inferences put into evidence the positive significant treatment effect for 7 companies.

Interpretation of the results from the ITTE sector is already partially done in the previous section 5.2.1, where we picked four companies from different regions and compared them with respect to the significance of the treatment effect. That is why we keep the description of the results of this sector short.

Computacenter Pl and *Pace Plc* show relatively poor performance. Their low RMSPE-ratios prove no significant improvement from the pre-treatment period, which is also approved by high p-values. *Vaisala Oyja Sh* has higher RMSPE-ratio, which means an improvement from the pre-treatment period, but unfortunately, the high p-values also give no significant treatment effects as for the two previous companies.

Dassault System, *Seagate Technolo*, *Akamai Technolog*, *Broadcom Corpa*, *Cognizant Techa*, and *Western Digital* are approved low significant. All of them have relatively high RMSPE-ratio, low pseudo p-value, but relatively high RMSPE-ratio p-value. On the other side, *Microchip Tech* outperforms other companies from its sector. The firm has high average treatment effect, very low RMSPE, highest RMSPE-ratio, and low both p-values. This company show significant treatment effect.

Health care sector

The health care sector contains 7 treated and 9 control units. Out of the 7 companies, 5 companies show decrease of CO_2 emissions per employee over the post-intervention period. And all of them are significant.

In comparison to other companies in the HC sector, *William Demant*, *BTG Plc*, and *Synergy Health* have relatively low RMSPE-ratios, proving not a great improvement compare to the pre-treatment period. On the other side, they do have low pseudo p-values, which approve a significant treatment effect. Thus we classify these three companies as low significant.

On the other side, *Actavis Plc* and *Celgene Corp* largely outperform other companies from the same sector in the values of the tests and are classified as highly significant. They have large RMSPE-ratios, indicating large decreases in CO_2 emissions per employee in the post-intervention period. The lowest possible pseudo p-values indicate that the positive treatment effect of the treated unit is not random. The high significant treatment effect is also approved by low placebo and RMSPE p-values, which means that other placebo-treated companies did not perform as well as the treated companies under investigation.

Financial sector

The financial sector, including 3 treated companies and 9 potential controls, performed relatively bad compare to the other sectors. For the three companies that were having a decrease in the CO2 emissions per employee in the post-treatment period, none of the treatment effects is proven to be significant.

5.3.3 Medium Carbon Dioxide emitters

The second group of the three sectors with medium carbon emissions comprises the CD, the CS, and the INDU sectors. These sectors are characterised by medium emissions compared to the other sectors, and relatively small values of the loss functions and the highest significant ratio of the treatment effect. In the following sections, we debrief the results of each firm.

Consumer Discretionary sector

Our data, restricted to the consumer discretionary sector, contain 10 treated and 12 control companies. We observed one extremely large treated company with pre-intervention RMSPE equal to 290 and for which we did not find a matching synthetic control. We have removed it from our analysis. The rest of the companies performed relatively well and got the pre-intervention RMSPE lower than 10, with the majority of them lower than 1. Out of the remaining 9 companies, 8 show decrease of CO2 emissions per employee over the post-intervention period. And our statistical inferences put into evidence the positive significant treatment effect for 4 companies.

In the table 5.4 we find the tests results for the eight companies with a positive average treatment effect. *Gtech Spa*, *Dignity Plc*, *Lowe's Cos Inc*, and *Vf Corp* show no improvement from the pre-treatment period, justify by low RMSPE-ratio and high RMSPE-ratio p-value. Thus, we reject the hypothesis of significant treatment effect for these four companies.

Valeo Sa, *Debenhams Plc*, and *Leggett & Platt* show low significant treatment effects. We observe relatively high RMSPE-ratios. Although for the *Leggett & Platt* the RMSPE-ratio p-value is quite high due to relatively high pre-treatment RMSPE. For the three companies we have low pseudo p-values which also confirm the low significant treatment effect.

Nokian Renkaat outperforms other companies in the sector and is classified as highly significant. In the annexe, the second firm of the figure A.13 presents the synthetic matching and permutation tests for this company. There is almost perfect match between the treated company and its synthetic control with respect to the CO2 emissions per employee. This result is confirmed by small pre-intervention RMSPE. We observe positive treatment effects, supported by high RMSPE-ratios. All placebo-treated units are sitting above the treated units under investigation, and having both low placebo and RMSPE p-values. As a consequence, there is a significant positive treatment effect for *Nokian Renkaat*.

Consumer Staples sector

Our data, restricted to the consumer staples sector, contains 12 treated and 16 control companies. We observed one extremely large treated company with relatively high pre-intervention RMSPE that was higher than 10 and we did not find a matching synthetic control. As the rest of the companies in the sector has the RMSPE lower than 5, we have considered this observation as extreme and removed it from our analysis. Out of the remaining 11 companies, 8 show decrease in CO2 emissions per employee over the post-intervention period. And our statistical inferences put into evidence the positive significant treatment effect for 7 companies, including 3 highly significant effects.

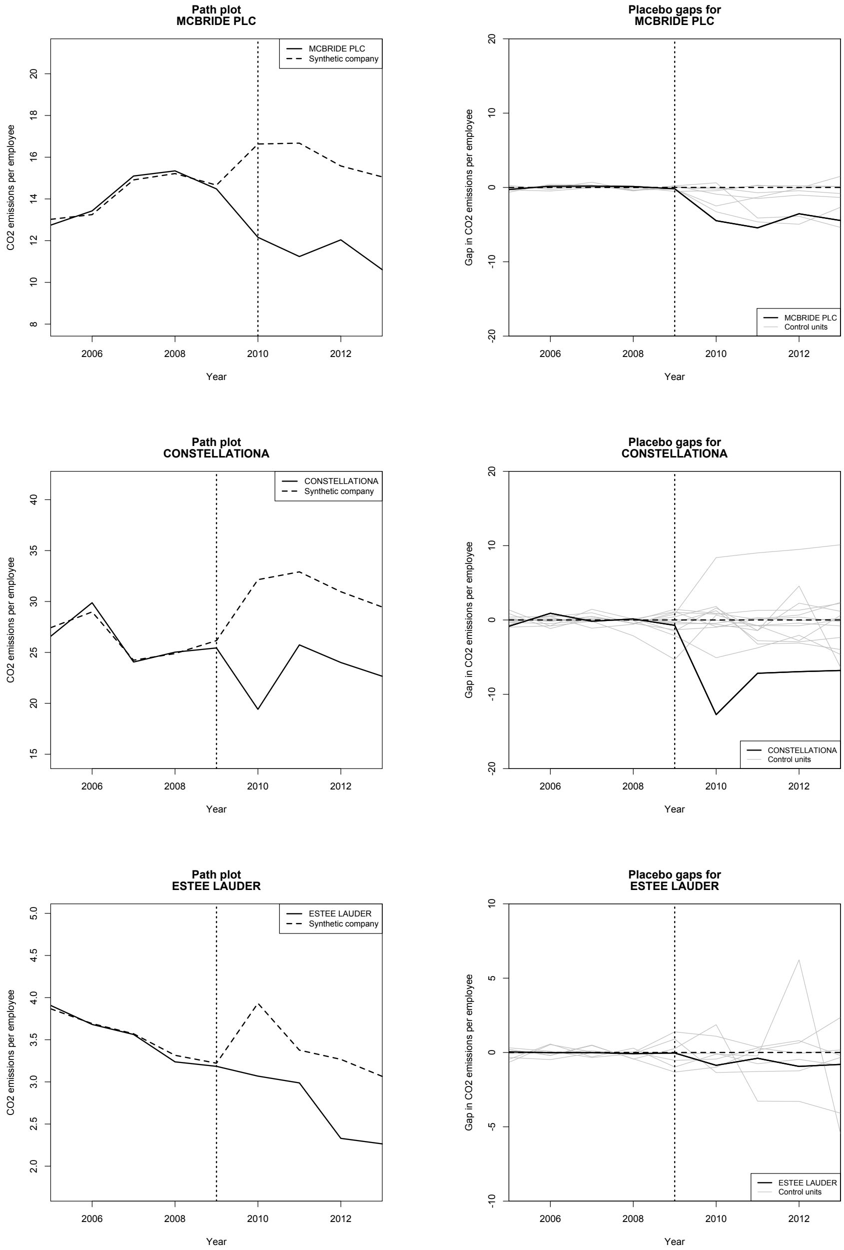
In the table 5.4, we find the statistical inference results for the eight companies with a positive average treatment effect. Only *Jeronimo Martins* shows quite a poor performance and no significant treatment effect. This is especially proven by the path plot and the placebo gaps plot (top graphs) on the figure A.14. Although all the statistics are relatively good for the company, we observe decreasing and then increasing gaps over the post-treatment period, which shows no effect of the treatment despite the good RMSPE's measures.

Grencore Group, *Koninkljke Phil*, *Hershey CO*, *Philip Morris* show low significant positive treatment effect. Compare to the other three companies, with highly significant treatment effect, they have relatively low RMSPE-ratios and relatively high RMSPE-ratio p-values. On the other side, the four companies have low pseudo p-values which confirm significant treatment effect.

Mcbride Plc, *Constellationa*, and *Estee Lauder* outperform the other companies in the values of the tests, and are classified as highly significant. The first column of figure 5.2 shows the graphs of the gaps of the CO2 emissions per employee for three treated companies and their synthetic controls. The path graphs indicate a good match between the treated company and its synthetic control with respect to the CO2 emissions per employee. This result is confirmed by small pre-treatment RMSPE for the three companies. The big gaps between the treated and synthetic control in post-treatment period indicate large treatment effects. These positive treatment effects are supported by high RMSPE-ratios, indicating large decreases in CO2 emissions per employee in the post-treatment period. On the placebo gaps graphs, during the post-treatment period, almost all placebo-treated units sit above the treated units under investigation. Thus the positive treatment effects of the treated units are not random. The results are affirmed by low placebo and RMSPE p-values. This means that the rest of the placebo-treated companies did not do as well as the treated companies under investigation.

Industrial sector

Our data, restricted to the industrial sector, contains 18 treated and 18 control companies. We observed 3 extremely large treated companies for which we did not find a matching synthetic control. Their pre-intervention RMSPEs were higher than 180. We have removed these cases from our analysis. The rest of the companies performed relatively well and got a pre-intervention RMSPE lower than 3. Out of the remaining 15 companies, 9 companies show decrease of CO2 emissions



Source: Author's elaboration.

Figure 5.2: Synthetic matching and permutation tests for Mcbride Plc, Constellationa, and Estee Lauder

per employee over the post-intervention period. And our statistical inferences put into evidence a positive significant treatment effect for only 7 companies, including 3 highly significant treatment effects.

In the table 5.4, we find the test results for the nine companies with a positive average treatment effect. *Centrotec Sustai* shows very poor RMSPE-ratio and its p-value prove no improvement from the pre-treatment period. Moreover, *DCC*'s high pseudo p-value rejects the hypothesis of significant treatment effect, despite the small RMSPE and relatively high RMSPE-ratio.

ABM Industries shows a very small decrease in CO2 emissions per employee, although with a poor pseudo p-value. We decided to classify it as a significant treatment, as it has relatively high RMSPE-ratio and the related p-value is the lowest possible. *Flsmith & CO*, *Kobenhavns Lufth* and *Kone Oyjb* show relatively good decreases in their CO2 emissions per employee, but have relatively small RMSPE-ratios, with high p-values indicating not a so great improvement from the pre-treatment period. On the other side, the low pseudo p-values prove no random effects. For these companies, we could confirm with placebo tests low significant and positive treatment effects.

On the other side, *Atlantia S.p.A.*, *Obracson Huarte* and *Serco Group* outperform the other companies, and are classified as highly significant. In the annexe A.5 we present the figures of the synthetic matching and permutation tests for these three companies. We see a good match between the treated company and its synthetic control with respect to the CO2 emissions per employee. This result is confirmed by small pre-intervention RMSPEs for all three companies. We observe positive treatment effects, supported by high RMSPE-ratios, indicating large decreases in CO2 emissions per employee in the post-intervention period for the three companies. We can also observe almost all placebo-treated units sitting above the treated units under investigation. This means that the positive treatment effect of the treated unit is not random. The results are affirmed by both low placebo and RMSPE p-values for all three companies, showing that other placebo-treated companies did not perform as well as the treated companies under investigation.

5.3.4 High Carbon Dioxide emitters

The last group of the three sectors with high carbon emissions includes the ENGY, the MATR, and the UTIL sectors. The high CO2 emitters are specific by very large greenhouse gas emissions. Moreover, the firms have relatively low number of employees, which leads to elevated values of the outcome variable. Another observation is the heterogeneity of the companies in the donor pool. These two arguments might be the reason for very high values of the loss function for the firms in these sectors that is an other of the characteristics of the group.

Note that for the three sectors the second model having the `GHG` as the outcome variable[12], was a bit more suited. This model gave relatively small values of the loss functions, but also always confirmed the results of the `GHG_EMP` model. Thus we kept the main model (`GHG_EMP`) for the analysis.

[12]Cf. section 4.3.1, presenting the alternative model.

As already mentioned, our data, restricted to the high CO_2 emitters, include energy, materials, and utility sectors. The data contain 11 treated and between 9 to 14 control companies (depending on respective sector). The companies performed relatively well in the matching process and got pre-intervention RMSPEs lower than 1.2[13]. Out of the 11 companies 5 show decrease of CO_2 emissions per employee over the post-intervention period. And our statistical inferences put into evidence the positive significant treatment effect for one company.

In the table 5.4, we find the statistical inference test results for the five companies with a positive average treatment effect. Four of them, *Saipem Spa*, *Enagas Sa*, *Cliffs Natural R*, and *Quest Diagnostic*, show very poor performance and no significant treatment effect. They have either low RMSPE-ratios or relatively high p-values, which reject the hypothesis of significant treatment effect.

On the other side, *Noble Enrgy Inc* outperforms other companies from the group and shows a low significant treatment effect. The firm has high RMSPE-ratio and low pseudo p-values, which prove no random treatment effect. For this company, we could affirm with placebo test low significant and positive treatment effect.

5.4 Conclusion

The objective of our study was to assess the pertinence of green policy introduction at the business level. In particular, we intended to evaluate whether signing up to the Carbon Disclosure Project, has a positive effect on companies' emissions. We used the synthetic control approach that allowed us to calculate the treatment effect for each of the companies under investigation, and perform statistical inferences at the same time. The conclusions about the suitability of the synthetic control method to study our problematic and the general observations about the method will be presented in the main conclusion. In this section, we make the statements on the three research questions.

First research question

"Is there a positive impact of the Carbon Disclosure Project on the participating firms?"

In total, out of the 73 companies that participate in the Carbon Disclosure Project, we have observed 6 companies with extremely large carbon emissions. These 6 companies were considered as outliers, and we did not include them for further analysis. Out of the remaining 67 companies, 48 revealed decrease of CO_2 emissions per employee after signing to the CDP. The placebo tests and the RMSPE indicators confirm low significant treatment effect for 21 companies and highly significant treatment effect for 10 companies. The remaining firms are considered either as having no treatment effects or showing no significant improvement.

[13] In order to make the results comparable to other sectors we lower the RMSPE by dividing the outcome variable (GHG_EMP) by 10.

Second research question

"Is there a difference of the impact on the international level, between European Union, United Kingdom, United States?"

The data distributed per regions, without the extreme values, contains 29 companies from the European Union, 16 from the United Kingdom, and 25 from the United States. We observe no effect for 7 firms from EU, 5 firms from UK, and 7 firms from US. Out of all companies with decreasing CO_2 emissions per employee after signing for the CDP program, we notice a significant change with respect to the pre-treatment period for 12, 5, and 14 companies from EU, UK, and US respectively. Which gives the highest success rate of 83% companies with the decreasing CO_2 emissions per employee for the United States.

Third research question

"Is there a difference in the impact between the sectors of activities?"

After exclusion of the extreme values, the data distributed per sectors contains 21 companies from the light emitters group, 35 companies from the middle emitters, which are the biggest group, and 11 firms only from the big carbon emitters group. The light emitters show the decrease in the CO_2 emissions per employee for 18 firms after the CDP entered into force, the middle emitters group show the decrease for 25 firms and the heavy emitters for 5 firms. This gives the highest success rate of 87% of companies achieving a decline in carbon emissions per employee to the light emitter. After the placebo tests, within the three groups, the light and middle emitters indicated much better performance than the heavy emitters which show low significant treatment effects for only one out of 11 treated companies. Significant treatment effects were revealed for 12 companies from the light emitters group and 18 from the medium carbon emitters group. Which gives a very close success rate of the program, 67% and 77% for the respective groups. Although, the medium emitters show slightly better performance in term of highly significant treatment effects. Concerning the individual sectors, we observed the highest success rates of the program after the placebo tests for the four following sectors: HC, ITTE, CS, and INDU.

Final conclusion

In conclusion, we found a decrease in CO_2 emissions per employee after the company starts to report to the Carbon Disclosure Project in about 70% of cases. So generally, there is a positive effect of the CDP on the firms' carbon performance. Moreover, the statistical inferences confirmed the significant treatment effect for 31 out of 48 companies that revealed decrease of CO_2 emissions per employee after signing to the CDP. Out of the three regions, United States seams to slightly outperform the other regions in the success of the program. And concerning the sectors, the middle emitters group shows a bit better performance in term of significant treatment effects. A final remark is that we observe significant and positive treatment effects for only half of the treated firms. This could be due to the fact that other non-participating companies are also under another strong institutional regulation of CO_2 emissions.

Conclusion

In our work, we covered different subjects. In the first chapter, we did a short literature review and introduced the main elements of the program evaluation methods. The second chapter covered the subject of the synthetic control method, which to our knowledge was not yet presented in one review in such an extend. The third chapter was dedicated to the environmental problematic. The fourth and fifth chapters covered the empirical part of our study. The chapter four set up the objectives of our study, and we presented the research questions, data and model implementation. And the chapter five showed the estimations and results and gave the answers to the three research questions.

The primary purpose of our study was to assess the effect of the CDP on the companies' emissions. To do so, we made use of the synthetic control methods that allowed us to generate the treatment effect for each of the studied companies, and perform statistical inferences. Moreover, for our analysis, we built a unique database containing high-quality data on the firm's characteristics, including the carbon dioxide emissions and other environmental indicators.

We have chosen the synthetic control method for different reasons. First of all, it allows researchers to analyse phenomena that occur in a limited population or that apply to only a small number of units. In our case, these units are firms, which is a situation perfectly suited to our problematic. Additionally, this method allows performing statistical inference analysis and supporting the results quantitatively. Several conclusions concerning the suitability of the method to our study have to be done.

First of all, using the synthetic control method allowed us to run individual company analysis. Which means that we did not have to use some general average measures per sector or country to estimate the treatment effects. For each firm, we could assess the impact of the program and make the statistical inferences, based on the specific company characteristics.

Second, we had to be careful while interpreting the results, because the size of the treatment effect was very proportionate to the size of the emissions. It means that in most of the cases, lower the emissions are, lower the size of the treatment effect is and vice versa. Though, the scope of the treatment effect was not the only measure showing the success of the program due to the heterogeneity of the companies. One could think that if we would have some normalisation of the quantitative characteristics of the firms, we could get more comparable firms in the pool. But we argue against the normalisation as it would not reflect the reality of the firms' behaviours. So, we need different measurements to quantify the treatment. It was very important in our case, to always look at all aspects of the analysis and measures that the SCM proposed. That is, we have to consider the size of the emissions and other firm's characteristics, the matchings, the loss functions, the graphs, the p-values, the RMSPEs indicators, or the ratios.

Third, we concluded that the model was very sensitive to the outliers. In our case, extreme values occurred by significant greenhouse gas emissions and relatively small number of employees, as well as relatively large values of other firms characteristics. The outliers had relatively large values of the loss functions, and we could not find matching control units. Consequently, we had to exclude the outliers from the analysis, as we could not give any appropriate interpretation of the results.

Fourth, we could approve that the model gave us a good quality match on the predictor variables. Also, the first goal of the method was always to make a good match between the outcome variables of the treated unit and its synthetic control. That is if there would be a big heterogeneity with respect to the CO2 emissions per employee between the treated unit and the units in donor pool, more weights would be given to the special predictors than to the rest of the predictors. We also observed that the match between the treated unit and its synthetic control was mostly much better that the match between the treated company and the average values of the predictors in the donor pool.

Fifth, sometimes the low number of observations in the donor pool, especially when there was a quite big heterogeneity between the observations in the donor pool on the treated unit, leads to high values of the loss functions under the random assignment.

Sixth, we noted that the value of the pre-treatment RMSPE is very individual and changes dramatically from one sector to other, that is why other synthetic control measurements helped to remain objective and give the not biased interpretation of the results. Moreover, the observations with relatively high values of the treatment effects have relatively low RMSPE-ratios, and the observations with relatively low RMSPE got relatively high RMSPE-ratios.

And finally, while doing the placebo tests, we observed that in the same sector of activities, that had the same donor pool, the synthetic control units for the placebo-treated companies remained mostly the same while changing the treated unit. This was another proof of the robustness of our model.

As already mentioned, the primary objective of our study was to assess the pertinence of green policy introduction at the business level. More precisely, we intended to evaluate whether participating in the Carbon Disclosure Project, as one of the binding reporting standards, has a positive effect on the firm's emissions. We also focussed on three different geographic regions, which are the European Union, the United Kingdom, and the United States. Furthermore, we compare the results between various sectors of activities.

In conclusion, we found that out of the 67 companies evaluated over 5 years and covering 9 sectors, even if the size of the effect varies on a case by case basis, the majority of the companies showed a positive effect of the CDP on the firms' environmental behaviour. Moreover, by the statistical inferences, we confirmed the significant treatment effect for half of the companies. Out of the three regions, even though the United States slightly outperformed the other regions in the success of the program, we did not find a big significant difference between the three regions (US, UK and EU). We could observe that the three studied regions are under strong regulation of CO2 emissions, amplified by large impact of the international agreements. This was also reflected in the quite good environmental performance of the other non-participating companies. Concerning the sectors of activities, inferior performance was shown by the high CO2 emitters. On the other side, the light and medium carbon emitters gave a very satisfying success rate of the program, with the middle emitters group showing slightly better performance in terms of significant treatment effects.

During our analysis, we encounter two issues. The first issue we faced concerned some approximated data for the greenhouse gas emissions. In most of the cases, we could solve the problem during the estimations. Thanks to the other firm's characteristics we could reestimate the emissions and make them more trustable. The second problem was related to a relatively short pre-treatment period to estimate the synthetic control units and a relatively short post-treatment period to evaluate the treatment effects. Keeping in mind that we would probably achieve higher quality estimation with a longer observation period, the use of the synthetic control method allows the estimation of the treatment effect in the case when only a few observations at the time are available. So we should not worry too much about the size of the observation period in our case.

We confirm that this method was well suited to our study, and could be used for further similar researches, as to analyse the introduction of other green policies or evaluation of disclosure methods. We could analyse whether the CDP firms achieved their target CO2 emissions. For this, the researcher should get extra information on what the target emission was. One could also collect data for more years or other regions and do an extensive study to prove the veracity of our results. Concerning the synthetic control method, we think that there could be some improvements done on the problematic of the outliers and estimations of the synthetic control units.

Appendix A

A.1 Basics behind matching and difference-in-differences methods

In this section, we present the basic idea behind matching and difference-in-differences (DID) methods. Note, that we have already introduced matching and difference-in-differences methods in section 1.2 as one of the methods that estimate the treatment effect under or without unconfoundedness. Since these two methods are used in the synthetic control method, the main method that we use in the empirical part to estimate the treatment effect and that will be presented in chapter 2, we would like to explain a bit more about the two methods in order to give some better understanding of chapter 2.

A.1.1 Matching methods

While estimating the treatment effect, we would like to compare the treated and control groups that are as similar as possible. Matching is one of the methods that helps us to find similar individuals. This method is used in two cases. In the first case, outcome variable isn't yet available, and the matching is used to select the subjects to follow up. In the second case, the outcome variable is already available, and the matching is used to estimate the causal effect and reduce selection bias in the estimate of the treatment effect.

Matching methods is performed in two steps. First, we have to determine the measure of distance ("closeness") to use in matching and then use the distance to execute the matching. In this section, we briefly present these two stages, and for more information see Stuart (2010), which is an excellent review of the matching methods.

Distance measures

The first estimation stage, determination of the measure of distance to be used in the matching, is proceeded in two steps. Firstly we choose the covariates to be included while relying on the strong ignorability assumption. Then secondly we combine the covariates into the distance measures, that is, measures of similarity between two individuals. Different distance measures exist. The most known are exact measure, Mahalanobis, propensity score or linear propensity score.

Here we present the four primary ways to define the distance ζ_{ij} between individuals i and j.

1. Exact distance

$$\zeta_{ij} = \begin{cases} 0 & \text{if} \quad C_i = C_j, \\ \infty & \text{if} \quad C_i \neq C_j. \end{cases}$$

2. Mahalanobis distance

$$\zeta_{ij} = (C_i - C_j)'\Sigma^{-1}(C_i - C_j),$$

where Σ is the variance covariance matrix of C (covariates) in the full control or treated group.

3. Distance based on propensity score

$$\zeta_{ij} = \left|e_i - e_j\right|,$$

where e_k is the propensity score for individual k (see Rosenbaum and Rubin (1985)).

4. Distance based on linear propensity score

$$\zeta_{ij} = \left|logit(e_i) - logit(e_j)\right|.$$

We have to point out that little is known about the optimal number of matches, or about data-dependent ways of choosing it. And that the most common distance metric used in practice to find the matches is the Mahalanobis metric, but there is also some very interesting alternative metrics that depend on the correlation between covariate, treatment assignment, and outcomes.

Matching methods

Once the distance measure has been selected, the following step is to use that distance to execute the matching. A spectrum of matching methods exists. One of the most common ones is the nearest neighbour matching method. The nearest neighbour matching includes methods as optimal matching, ratio matching and matching with or without replacement. Another class of methods includes sub-classifications, full matching and weighting.

Note that the matching methods are not themselves methods for estimating causal effects. After the matching has created treated and control groups with adequate balance, we can move to the outcome analysis stage. Depending on the choice of the matching methods, this stage involves, for example, the regression methods, propensity score methods, DID, and many others, depending on the choice of the matching methods.

A.1.2 Difference-in-differences methods

As we presented before, matching is one of the methods that controls for observed confounding vectors and minimises the selection bias. If important confounders are unobserved, we can get the causal effect by using instrumental variables. Another way to deal with unobserved confounders is to use panel data and the fixed effects methods, or it's extended version of the difference-in-differences method or fixed effect with lagged dependent variable presented in this section.

Fixed effect model

In the observational study, while constructing the treatment effect, we face the problem of heterogeneous treated and control units. Many of the factors that make the difference will not be observable, and so we face the standard omitted variable bias (OVB) problem, as we now define.

Definition A.1 (Omitted variable bias)**.**

OVB occurs when we incorrectly left out one or more important control variables when the model is created. The bias occurs when the model compensates for the missing factor by over or underestimating the effect of one of the other factors.

Individual level panel data is a powerful tool for estimating treatment effect and deal with the OVB. To estimate the treatment effect we can use the fixed effect strategy that requires panel data, that is, repeated observations on the same individuals. This means that we have n individuals and T time periods. Let $i = 1,...,n$ be an individual, who decides whether to participate in the program and $t = 1,...,T$ a period of time. Furthermore, the fixed effect model contains the following variables: Y_{it}, potential outcome of individual i at the time period t, D_{it}, causal exposure variable for individual i at time period t, C_{it}, time varying and observed covariates and A_i, unobserved but fixed confounders.

We are interested in the causal effect estimation, which is the difference between the treated and control outcome variables. Because of the fundamental problem of causal inferences we have to estimate the potential outcome for the control group. We suppose that $E[Y_{it}^N \mid A_i, C_{it}, t, D_{it}] = E[Y_{it}^N \mid A_i, C_{it}, t]$ and so we can define the expected potential outcome of the controls as follow:

$$E[Y_{it}^N \mid A_i, C_{it}, t] = \alpha + \lambda_t + A_i'\pi + C_{it}'\theta. \tag{A.1}$$

Assuming that the causal effect of the treated is additive and constant we have the following expected potential outcome of the treated:

$$E[Y_{it}^I \mid A_i, C_{it}, t] = E[Y_{it}^N \mid A_i, C_{it}, t] + \delta. \tag{A.2}$$

The equations (A.1), (A.2) imply:

$$E[Y_{it} \mid A_i, C_{it}, t] = \alpha + \lambda_t + \delta D_{it} + A_i'\pi + C_{it}'\theta,$$

where δ is the causal effect of interest.

Putting all together, this implies the following regression equation, which is the fixed-effect model:

$$Y_{it} = \alpha_i + \lambda_t + \delta D_{it} + C_{it}'\theta + \varepsilon_{it},$$

where $\varepsilon_{it} = Y_{it}^N - E[Y_{it}^N \mid A_i, C_{it}, t]$ and $\alpha_i = \alpha + A_i'\pi$. If we estimate this model with simple ordinary least squares without including individual fixed effects, α_i will be correlated with D_{it} and so the D_{it} will be correlated with the error term and this will lead to biased ordinary least squares estimates. In practice, there are two ways to estimate the fixed effects model: within estimator or first differencing, presented in following equations:

1. Within estimator:

$$Y_{it} - \bar{Y}_i = \lambda_t - \bar{\lambda} + \delta(D_{it} - \bar{D}_i) - (C_{it} - \bar{C}_i)'\theta + (\varepsilon_{it} - \bar{\varepsilon}_i).$$

2. First differencing:

$$\Delta Y_{it} = \Delta\lambda_t + \delta\Delta D_{it} - \Delta C_{it}'\theta + \Delta\varepsilon_{it},$$

where prefix Δ denotes the change from one period to the next one, for exemple $\Delta Y_{it} = Y_{it} - Y_{it-1}$.

Both methods drop out the α_i, and therefore the error term and the regressor would no longer be correlated. With two periods, the two methods are algebraically the same, but otherwise not. Both methods should work, but with first differencing, we introduce serial correlation of the error terms. Therefore within estimator would be more likely the better option.

Difference-in-differences

As we already mentioned, the fixed effect strategy requires panel data. But if only the aggregate data are available, the option is to use the difference-in-differences methods, a version of fixed-effect estimation using aggregate data. Since the work by Ashenfelter and Card (1985), the use of difference-in-differences methods has become quite widespread.

The simplest setting of the DID model is one where the outcome is observed for units that are observed in one of two groups, and in one of two time periods. Only units in one of the two groups are exposed to treatment in the second time period. None of the units is exposed to the treatment in the first period, and units from the control group are never exposed to the treatment. The average gain over time in the control group is subtracted from the gain over time in the treatment group. Imbens and Wooldridge (2008, p. 64) states: *"This double differencing removes biases in second period comparisons between the treatment and control group that could be the result of permanent differences between those groups, as well as biases from comparisons over time in the treatment group that could be the result of time trends unrelated to the treatment."*

Let i be the individual that belongs to the group $g_i \in N, I$ (where group N is the control and I is the treatment), and is observed in time period $t_i \in 0, 1$. Then we can define the expected potential outcome for the controls as follows:

$$E[Y_i^N \mid g, t] = \gamma_g + \lambda_t,$$

where γ_g is time invariant group effect and λ_t time effect that is common across groups.

Let D_{gt} be the causal exposure variable for group g at time t. Assuming that $E[Y_i^I - Y_i^N \mid g, t] = \delta$ is the treatment effect, in the standard DID model we can write the outcome for individual i in the absence of intervention, Y_i^N as:

$$Y_i^N = \gamma_g + \lambda_t + \delta D_{gt} + \varepsilon_i,$$

where the term ε_i represents unobservable characteristics of the individuals. Then the standard DID estimands of the treatment effect is equal to:

$$\begin{aligned}\delta_{did} &= E[Y_i^I \mid D_i = 1] - E[Y_i^N \mid D_i = 0] \\ &= (E[Y_i \mid g_i = I, t_i = 1] - E[Y_i \mid g_i = I, t_i = 0]) \\ &\quad -(E[Y_i \mid g_i = N, t_i = 1] - E[Y_i \mid g_i = N, t_i = 0]).\end{aligned}$$

In other words, to get the DID estimands of the treatment effect, the population average difference over time in the control group is subtracted from the population average difference over time in the treatment group to remove biases associated with a common time trend underrated to the intervention. Common time trend under non-treatment is the key assumption for any DID strategy. It is the outcome in treatment and control group that would follows the same time trend in the absence of the treatment. Note, that this does not mean that they have the same mean of the outcome. Common trend assumption is difficult to verify but one often uses pre-treatment data to show that the trend are the same.

To conclude this chapter, we have to mention different important remarks concerning the DID model. The first remark is that the two periods and two groups problem can be easily extended to the multiple periods and multiple groups.

Second, we can also estimate the difference-in-differences estimator in a regression framework. Angrist and Pischke (2008) defend the regression framework and presents following advantages: it's easy to calculate standard errors, to control for other variables which may reduce the residual variance, easy to include multiple periods, to study treatments with different treatment intensity.

Third, one can use lagged dependent variables over h[14] periods of time, Y_{it-h}, in the estimation so the conditional independence assumption become: $E[Y_{it}^N \mid A_i, Y_{it-h}, C_{it}, t, D_{it}] = E[Y_{it}^N \mid A_i, Y_{it-h}, C_{it}, t]$, and the term Y_{it-h} is introduced in the modelling.

A final remark is that in some cases, treatment and potential control groups do not follow parallel trends and so the standard DID methods would lead to biased estimates. Abadie and Gardeazabal (2003) pioneered a synthetic control method when estimating the effects of the terrorist conflict in the Basque Country using a combination of other Spanish regions as a comparison group. The basic idea behind the synthetic control is that a combination of units often provides a better comparison for the unit exposed to the intervention than any single unit alone. The synthetic control method is presented in chapter 2.

[14] In this case, $h > 1$, otherwise one gets the unconfoundedness case for matching.

A.2 Sectors descriptions

The description is extracted from Carbon Diclosure Project (CDP) (2014a).

Energy Sector: The GICS Energy Sector comprises companies whose businesses are dominated by either of the following activities: The construction or provision of oil rigs, drilling equipment and other energy related service and equipment, including seismic data collection. Companies engaged in the exploration, production, marketing, refining and/or transportation of oil and gas products.

Materials Sector: The GICS Materials Sector encompasses a wide range of commodity-related manufacturing industries. Included in this sector are companies that manufacture chemicals, construction materials, glass, paper, forest products and related packaging products and metals, minerals and mining companies, including producers of steel.

Industrials Sector: The GICS Industrials Sector includes companies whose businesses are dominated by one of the following activities: The manufacture and distribution of capital goods, including aerospace & defence, construction, engineering & building products, electrical equipment and industrial machinery. The provision of commercial services and supplies, including printing, employment, environmental and office services. The provision of transportation services, including airlines, couriers, marine, road & rail and transportation infrastructure.

Consumer Discretionary Sector: The GICS Consumer Discretionary Sector encompasses those industries that tend to be the most sensitive to economic cycles. Its manufacturing segment includes automotive, household durable goods, textiles & apparel and leisure equipment. The services segment includes hotels, restaurants and other leisure facilities, media production and services and consumer retailing.

Consumer Staples Sector: The GICS Consumer Staples Sector comprises companies whose businesses are less sensitive to economic cycles. It includes manufacturers and distributors of food, beverages and tobacco and producers of non-durable household goods and personal products. It also includes food & drug retailing companies as well as hypermarkets and consumer supercenters.

Health Care Sector: The GICS Health Care Sector encompasses two main industry groups. The first includes companies who manufacture health care equipment and supplies or provide health care related services, including distributors of health care products, providers of basic health-care services and owners and operators of health care facilities and organisations. The second regroups companies primarily involved in the research, development, production and marketing of pharmaceuticals and biotechnology products.

Financials Sector: The GICS Financial Sector contains companies involved in activities such as banking, mortgage finance, consumer finance, specialised finance, investment banking and brokerage, asset management and custody, corporate lending, insurance, financial investment and real estate, including REITs.

Information Technology Sector: The GICS Information Technology Sector covers the following general areas: First, Technology Software & Services, including companies that primarily develop software in various fields such as the Internet, applications, systems, database management and/or home entertainment and companies that provide information technology consulting and services as well as data processing and outsourced services; second, Technology Hardware & Equipment, including manufacturers and distributors of communications equipment, computers & peripherals, electronic equipment and related instruments, and third, Semiconductors and Semiconductor Equipment Manufacturers.

Telecommunications Services Sector: The GICS Telecommunications Services Sector contains companies that provide communications services primarily through a fixed-line, cellular, wireless, high bandwidth and/or fiber optic cable network.

Utilities Sector: The GICS Utilities Sector encompasses those companies considered electric, gas or water utilities or companies that operate as independent producers and/or distributors of power. This sector includes both nuclear and non-nuclear facilities.

A.3 Data descriptives

Variables	Description
ID	Company's identification number (numeric);
NAME	Company's name (nominal);
CDP_IN	Indicator variable defining if the company is reporting to the CDP (0: not reporting, 1: reporting) (numeric);
CDP_YEAR	The year the company started to report between 2003 – 2013, is NA if the company does not report (numeric);
COUNTRY	Company's headquarter (nominal);
SECTOR	Company's sector (nominal);
INDUSTRY_SECTOR	Company's industry (nominal);
SUB_INDUSTRY	Company's sub-industry (nominal);
CLIMAT_CDP	The year the company started to report to the CDP Climat change program, concerns only the period between 2003 – 2013, is NA if the company does not report (numeric);
WATER_CDP	The year the company started to report to the CDP Water program, concerns only the period between 2003 – 2013, is NA if the company does not report (numeric);
SUPPLY_CHAIN_CDP	The year the company started to report to the CDP Supply chain program, concerns only the period between 2003 – 2013, is NA if the company does not report (numeric);
FOREST_CDP	The year the company started to report to the CDP Forest program, concerns only the period between 2003 – 2013, is NA if the company does not report (numeric);
GHG05 - GHG13	Company's greenhouse gas emissions in metric tons for the years 2005 – 2013 (numeric);
S05 - S13	Source of the reported company's greenhouse gas for the years 2005 – 2013;
R05 - R013	Company's revenue in mio CHF for the years 2005 – 2013 (numeric);
GP05 - GP13	Company's gross profit in mio CHF for the years 2005 – 2013 (numeric);
COGS05 - COGS13	Company's cost of goods sold in mio CHF for the years 2005 – 2013 (numeric);
FA05 - FA13	Company's fixed assets in mio CHF for the years 2005 – 2013 (numeric);
EMP05 - EMP13	Company's number of employees for the years 2005 – 2013 (numeric);
P05 - P13	Company's share price in CHF for the years 2005 – 2013 (numeric);
RI05 - RI13	Company's return on investment in CHF for the years 2005 – 2013 (numeric);
KL05 - KL13	Company's capital-labor ratio for the years 2005 – 2013 (numeric);
GHG_EMP05 - GHG_EMP13	Company's greenhouse gas emissions in metric tons per employee for the years 2005 – 2013 (numeric);

Source: Author's elaboration.

Table A.1: Variables in the transversal database

```
  [1] "ABM INDUSTRIES"      "ACS"                     "ACTAVIS PLC"         "AECOM TECHNOLOGY"
  [5] "AGCO CORP"           "AGGREKO PLC"             "AKAMAI TECHNOLOG"    "ALASKA AIR GROUP"
  [9] "ALBEMARLE CORP"      "AMEC FOSTER WHEE"        "ANTOFAGASTA PLC"     "AP MOELLERB"
 [13] "AQUA AMERICA INC"    "ATLANTIA SPA"            "AVON RUBBER"         "BANCO COM PORTR"
 [17] "BAVARIAN NORDIC"     "BLOOMSBURY PUBL"         "BOOKER GROUP PLC"    "BROADCOM CORPA"
 [21] "BTG PLC"             "CABOT CORP"              "CAMPBELL SOUP CO"    "CARDINAL HEALTH"
 [25] "CARILLION PLC"       "CELGENE CORP"            "CENTROTEC SUSTAI"    "CHEMRING GROUP"
 [29] "CHIME COMMUNICAT"    "CINEWORLD GROUP"         "CLIFFS NATURAL R"    "COGNIZANT TECHA"
 [33] "COMPUTACENTER PL"    "CONSTELLATIONA"          "CR BARD INC"         "CREDIT AGRICOLE"
 [37] "DASSAULT SYSTEME"    "DCC PLC"                 "DEBENHAMS PLC"       "DELTA AIR LI"
 [41] "DIGNITY PLC"         "DLH A/S"                 "DRESSERNRAND GRO"    "ENAGAS SA"
 [45] "ENCE ENERGIA Y C"    "ERAMET"                  "ESTEE LAUDER"        "FALCK RENEWABLES"
 [49] "FIAT CHRYSLER AU"    "FIDESSA GROUP PL"        "FISHER (JAMES)"      "FLOWERS FOODS"
 [53] "FLSMIDTH & CO"       "FLUIDRA SA"              "FRIGOGLASS SAIC"     "FROMAGERIES BEL"
 [57] "FUTURE PLC"          "GENERALI ASSIC"          "GREENCORE GROUP"     "GREIF INCCL A"
 [61] "GTECH SPA"           "HANSTEEN HOLDING"        "HARLEYNDAVIDSON"     "HELLENIC PETRO"
 [65] "HELLENIC TELECOM"    "HERSHEY CO/THE"          "HORMEL FOODS CRP"    "HOWDEN JOINERY G"
 [69] "HUNTSMAN CORP"       "IHS INCNCLASS A"         "INTERCONTINENTAL"    "JARDINE LLOYD TH"
 [73] "JERONIMO MARTINS"    "JETBLUE AIRWAYS"         "KBR INC"             "KOBENHAVNS LUFTH"
 [77] "KONE OYJB"           "KONINKLIJKE PHIL"        "KRKA"                "LEGGETT & PLATT"
 [81] "LENNOX INTL INC"     "LIBERTY GLOBALNA"        "LOWE'S COS INC"      "MACERICH CO"
 [85] "MARVELL TECH GRP"    "MCBRIDE PLC"             "MELIA HOTELS INT"    "MERCIALYS"
 [89] "MICROCHIP TECH"      "MOHAWK INDS"             "MOSAIC CO/THE"       "NOBLE ENERGY INC"
 [93] "NOKIAN RENKAAT"      "OBRASCON HUARTE"         "ODET"                "OMV PETROM SA"
 [97] "OSHKOSH CORP"        "PACE PLC"                "PATRIZIA IMMOBIL"    "PHILIP MORRIS IN"
[101] "PROSEGUR"            "PVH CORP"                "PZ CUSSONS PLC"      "QUEST DIAGNOSTIC"
[105] "RAISIO OYJNV"        "RENREDE ENERGET"         "RESTAURANT GROUP"    "SACYR SA"
[109] "SAIPEM SPA"          "SAVILLS PLC"             "SCHNITZER STEEL"     "SEAGATE TECHNOLO"
[113] "SECHE ENVIRONNEM"    "SENIOR PLC"              "SERCO GROUP"         "SL GREEN REALTY"
[117] "SONAE"               "SOUTHWEST AIR"           "SUNPOWER CORP"       "SYNERGY HEALTH P"
[121] "TESORO CORP"         "TIMBERLAND BANCORP INC" "TULLETT PREBON P"    "TUPPERWARE BRAND"
[125] "ULTRA ELECTRONIC"    "VAISALA OYJA SH"         "VALEO SA"            "VESUVIUS PLC"
[129] "VF CORP"             "VOPAK"                   "WATERS CORP"         "WESTERN DIGITAL"
[133] "WILLIAM DEMANT"      "XAAR PLC"                "ZODIAC AEROSPACE"
```

Source: Author's elaboration.

Table A.2: Company's names

ID2	YEAR	NAME
100	2009	AP MOELLERB
CDP	COUNTRY	SECTOR
1	Denmark	Industrials
INDUSTRY_SECTOR	SUB_INDUSTRY	CLIMAT_CDP
Marine	Marine	1
WATER_CDP	SUPPLY_CHAIN_CDP	FOREST_CDP
0	0	0
GHG	S	R
40488998	CSR	52777
GP	COGS	FA
43178	9598	77102
EMP	P	RI
115386	1412	1039
KL	GHG_EMP	
668213	732	

Source: Author's elaboration.

Table A.3: One observation from the data

```
CDP_YEAR
      n missing  unique
    142       0       3

2009 (42, 30%), 2010 (34, 24%), N (66, 46%)

COUNTRY
      n missing  unique
    135       0      14

          Denmark Finland France Germany Greece Ireland Italy Netherlands Portugal
Frequency       6       3      9       2      3       3     6           2        4
%               4       2      7       1      2       2     4           1        3
          Romania Slovenia Spain UK US
Frequency       1        1     8 34 53
%               1        1     6 25 39

INDUSTRY_SECTOR
      n missing  unique
    135       0      57

SUB_INDUSTRY
      n missing  unique
    135       0      85

CLIMAT_CDP
      n missing  unique
    135       0       4

2009 (41, 30%), 2010 (30, 22%), 2011 (1, 1%), NA (63, 47%)

WATER_CDP
      n missing  unique
    135       0       5
2010 (3, 2%), 2011 (3, 2%), 2012 (6, 4%), 2013 (2, 1%), NA (121, 90%)

SUPPLY_CHAIN_CDP
      n missing  unique
    135       0       5

2010 (6, 4%), 2011 (7, 5%), 2012 (8, 6%), 2013 (5, 4%), NA (109, 82%)

FOREST_CDP
      n missing  unique
    135       0       3

2012 (4, 3%), 2013 (1, 1%), NA (130, 96%)
```

Source: Author's elaboration.

Table A.4: Descriptive statistics for different variables - Transversal database

	CD	CS	ENGY	FINA	HC	INDU	IT	MATR	TC	UTIL	Sum
Denmark	0	0	0	0	2	3	0	1	0	0	6
Finland	1	0	0	0	0	1	1	0	0	0	3
France	1	1	0	2	0	3	1	1	0	0	9
Germany	0	0	0	1	0	1	0	0	0	0	2
Greece	0	1	1	0	0	0	0	0	1	0	3
Ireland	0	1	0	0	0	1	1	0	0	0	3
Italy	2	0	1	1	0	1	0	0	0	1	6
Netherlands	0	1	1	0	0	0	0	0	0	0	2
Portugal	0	2	0	1	0	0	0	0	0	1	4
Romania	0	0	1	0	0	0	0	0	0	0	1
Slovenia	0	0	0	0	1	0	0	0	0	0	1
Spain	1	0	0	0	0	5	0	1	0	1	8
UK	10	3	1	4	2	9	4	1	0	0	34
US	7	7	3	3	5	12	6	7	0	3	53
Sum	22	16	8	12	10	36	13	11	1	6	135

Source: Author's elaboration.

Table A.5: Cross-table country and sector for all countries

	CD	CS	ENGY	FINA	HC	INDU	IT	MATR	TC	UTIL	Sum
Denmark	0	0	0	0	1	3	0	1	0	0	5
Finland	1	0	0	0	0	1	1	0	0	0	3
France	1	0	0	0	0	0	1	0	0	0	2
Germany	0	0	0	0	0	1	0	0	0	0	1
Greece	0	0	0	0	0	0	0	0	1	0	1
Ireland	0	1	0	0	0	1	1	0	0	0	3
Italy	1	0	1	1	0	1	0	0	0	0	4
Netherlands	0	1	1	0	0	0	0	0	0	0	2
Portugal	0	2	0	1	0	0	0	0	0	1	4
Romania	0	0	0	0	0	0	0	0	0	0	0
Slovenia	0	0	0	0	0	0	0	0	0	0	0
Spain	1	0	0	0	0	2	0	0	0	1	4
UK	3	2	0	1	2	5	2	1	0	0	16
US	3	6	1	0	4	4	6	3	0	1	28
Sum	10	12	3	3	7	18	11	5	1	3	73

Source: Author's elaboration.

Table A.6: Cross-table country and sector for participating countries

	CD	CS	ENGY	FINA	HC	INDU	IT	MATR	TC	UTIL	Sum
Denmark	0	0	0	0	1	0	0	0	0	0	1
Finland	0	0	0	0	0	0	0	0	0	0	0
France	0	1	0	2	0	3	0	1	0	0	7
Germany	0	0	0	1	0	0	0	0	0	0	1
Greece	0	1	1	0	0	0	0	0	0	0	2
Ireland	0	0	0	0	0	0	0	0	0	0	0
Italy	1	0	0	0	0	0	0	0	0	1	2
Netherlands	0	0	0	0	0	0	0	0	0	0	0
Portugal	0	0	0	0	0	0	0	0	0	0	0
Romania	0	0	1	0	0	0	0	0	0	0	1
Slovenia	0	0	0	0	1	0	0	0	0	0	1
Spain	0	0	0	0	0	3	0	1	0	0	4
UK	7	1	1	3	0	4	2	0	0	0	18
US	4	1	2	3	1	8	0	4	0	2	25
Sum	12	4	5	9	3	18	2	6	0	3	62

Source: Author's elaboration.

Table A.7: Crosstable country and sector for non-participating countries

Variables	Mean	Median	Std. Dev.	Min.	Max.	N
CDP companies						
GHG	824508	246841	1043881	22000	3245900	90
R	9001	3286	14776	298	58642	90
COGS	5989	2262	9870	126	38400	90
EMP	35907	18368	44806	2270	166000	90
KL	221375	179196	221042	29618	1199210	90
GHG_EMP	49	11	93	4	359	90
Non-CDP companies						
GHG	545089	71000	1073052	302	4383000	108
R	9306	1861	22192	120	103000	108
COGS	7105	767	19015	59	88012	108
EMP	25064	7411	52145	292	225587	108
KL	165449	90748	231528	13338	996569	108
GHG_EMP	15	11	17	1	76	108

Source: Author's elaboration.

Table A.8: Summary statistics (panel data on 9 years) sector "Consumer Discretionary"

Variables	Mean	Median	Std. Dev.	Min.	Max.	N
CDP companies						
GHG	501042	295647	460431	51954	2612602	108
R	9918	7207	10384	1080	44026	108
COGS	5589	3977	6052	639	28996	108
EMP	32757	19200	34732	4120	159226	108
KL	170534	1436941	98215	52855	424754	108
GHG_EMP	22	15	18	2	77	108
Non-CDP companies						
GHG	189811	50298	146295	22563	444211	36
R	2827	2756	1997	159	7168	36
COGS	2195	1513	2012	149	6956	36
EMP	8398	8650	2152	4209	11832	36
KL	185208	134771	365228	36629	2274356	36
GHG_EMP	21	16	15	5	50	36

Source: Author's elaboration.

Table A.9: Summary statistics (panel data on 9 years) sector "Consumer Staples"

Variables	Mean	Median	Std. Dev.	Min.	Max.	N
CDP companies						
GHG	1387853	1343336	89113	279000	294419	27
R	6182	3509	5741	1059	16475	27
COGS	1940	1458	1593	352	5024	27
EMP	13768	3707	16508	1171	48607	27
KL	3397249	1382298	3744035	258198	9525704	27
GHG_EMP	553	92	729	31	2049	27
Non-CDP companies						
GHG	2773680	2499053	2571238	29941	8939025	45
R	9405	6737	9430	207	34850	45
COGS	8294	4430	8951	167	32044	45
EMP	9530	5400	11700	742	49553	45
KL	712564	355264	705425	57822	26980143	45
GHG_EMP	589	621	524	5	1848	45

Source: Author's elaboration.

Table A.10: Summary statistics (panel data on 9 years) sector "Energy"

Variables	Mean	Median	Std. Dev.	Min.	Max.	N
CDP companies						
GHG	55468	65739	41432	1910	122680	27
R	2825	1045	3344	99	9991	27
COGS	2713	986	3276	66	9771	27
EMP	39273	22001	27380	14516	85368	27
KL	4510915	5823547	3403289	4252	9419665	27
GHG_EMP	2	1	2	0.1	4	27
Non-CDP companies						
GHG	82312	12021	169343	228	594287	81
R	5332	728	13448	27	49073	81
COGS	3277	323	8406	4	33597	81
EMP	10470	1045	25517	6	89172	81
KL	10649346	3215802	14127956	11145	58158299	81
GHG_EMP	72	16	100	0.2	485	81

Source: Author's elaboration.

Table A.11: Summary statistics (panel data on 9 years) sector “Financial”

Variables	Mean	Median	Std. Dev.	Min.	Max.	N
CDP companies						
GHG	87714	33083	121162	2226	381000	63
R	15825	1626	34869	86	108000	63
COGS	14145	358	33434	53	103000	63
EMP	8775	5000	11881	67	55000	63
KL	140775	128260	77657	55557	509709	63
GHG_EMP	12	11	9	1	42	63
Non-CDP companies						
GHG	51346	42722	43863	4188	152132	27
R	1340	1377	1077	15	2835	27
COGS	520	515	406	14	1107	27
EMP	6405	7975	4722	224	13000	27
KL	204261	220762	132395	45626	559912	27
GHG_EMP	12	15	6	3	26	27

Source: Author's elaboration.

Table A.12: Summary statistics (panel data on 9 years) sector “Health Care”

Variables	Mean	Median	Std. Dev.	Min.	Max.	N
CDP companies						
GHG	6111641	144091	12874994	14609	56739464	162
R	9771	4832	13837	98	66400	162
COGS	5521	3265	7179	93	41117	162
EMP	35632	13901	41887	788	164750	162
KL	315720	102529	448624	1376	2173789	162
GHG_EMP	316	14	1040	1	7431	162
Non-CDP companies						
GHG	607549	110822	1199739	3138	5988837	162
R	4317	3748	3223	105	13137	162
COGS	3260	2229	2964	37	12314	162
EMP	20851	14059	25326	718	154514	162
KL	133214	67774	161174	2370	605604	162
GHG_EMP	70	8	143	0.2	546	162

Source: Author's elaboration.

Table A.13: Summary statistics (panel data on 9 years) sector "Industrial"

Variables	Mean	Median	Std. Dev.	Min.	Max.	N
CDP companies						
GHG	220468	59276	347331	1998	1300000	63
R	4348	3037	3774	307	14454	63
COGS	2625	1581	2862	69	11304	63
EMP	22755	7939	32510	595	171400	63
KL	167638	108208	175311	8273	763078	63
GHG_EMP	14	7	17	1	101	63
Non-CDP companies						
GHG	4254	3872	1346	2421	6079	27
R	219	181	133	70	411	27
COGS	167	116	128	36	348	27
EMP	854	640	565	260	738	27
KL	133900	160258	61515	65079	227824	27
GHG_EMP	6	6	3	3	10	27

Source: Author's elaboration.

Table A.14: Summary statistics (panel data on 9 years) sector "Information technology and telecomunication"

Variables	Mean	Median	Std. Dev.	Min.	Max.	N
CDP companies						
GHG	276568	265309	68213	190056	4770009	27
R	3147	1272	3085	564	8090	27
COGS	1558	324	2027	0.2	4764	27
EMP	14581	1031	19748	584	43500	27
KL	4796959	6907469	4422537	1603	11384492	27
GHG_EMP	217	269	161	6	434	27
Non-CDP companies						
GHG	2682301	222132	3682312	43188	9842151	27
R	222436	681	320146	127	695000	27
COGS	13159	562	24469	85	77726	27
EMP	1028	1330	663	140	1896	27
KL	2604853	2561552	2092489	262914	77724328	27
GHG_EMP	2131	1542	2116	23	6030	27

Source: Author's elaboration.

Table A.15: Summary statistics (panel data on 9 years) sector “Utilities”

Variables	Mean	Median	Std. Dev.	Min.	Max.	N
CDP companies						
GHG	3474314	3677795	3675338	3715	9320000	45
R	4167	3229	2844	358	11518	45
COGS	2819	2295	2128	319	8424	45
EMP	4886	4370	2153	473	8500	45
KL	836972	762177	533283	38346	1689423	45
GHG_EMP	643	516	485	2	1745	45
Non-CDP companies						
GHG	2310130	1330000	1829647	432121	6650000	54
R	4218	3157	3214	795	13310	54
COGS	3346	2764	2778	317	11296	54
EMP	7871	6252	5163	1048	15741	54
KL	531435	489851	338972	130739	1592713	54
GHG_EMP	322	305	134	77	590	54

Source: Author's elaboration.

Table A.16: Summary statistics (panel data on 9 years) sector “Materials”

A.4 Results of the synthetic control analysis in R

```
# 2.1. Run the synth command to identify optimal weights (see Remarque Synth)

> synth(dataprep.out)

X1, X0, Z1, Z0 all come directly from dataprep object.


****************
 searching for synthetic control unit


****************
****************
****************

MSPE (LOSS W): 0.00017517
MSPE (LOSS V): 0.02834802

solution.v:
 3.58464e-05 0.0003637101 0.0001761632 0.3505531 0.0002139565 0.0004261314
 7.57813e-05 0.04520849 0.1585999 0.07461483 0.1847113 0.1850208

solution.w:
 0.0007608 0.000728132 0.1799323 0.1262085 0.5895293 0.0009608754 0.001070103
 0.0001224718 0.0001216348 0.01529448 0.001251224 0.08402018
```

Source: Author's elaboration.

Figure A.3: Results of the function synth() for company "DEBENHAMS"

```
# 2.2 Compute the gaps

> print(gaps)
              403
2005  0.122113871
2006  0.008454128
2007  0.112171278
2008 -0.292961475
2009  0.193088601
2010 -1.006822614
2011 -0.569185343
2012 -0.642107052
2013 -1.563949296
```

Source: Author's elaboration.

Figure A.4: Treated effects for company "DEBENHAMS"

```
# 2.3.1 Summary tables

print(synth.tables)

$tab.w
     w.weights       unit.names unit.numbers
218      0.001  BLOOMSBURY PUBL          218
308      0.001 CHIME COMMUNICAT          308
321      0.180  CINEWORLD GROUP          321
517      0.126 FIAT CHRYSLER AU          517
548      0.590       FUTURE PLC          548
612      0.001  HARLEYNDAVIDSON          612
649      0.001 HOWDEN JOINERY G          649
816      0.000 LIBERTY GLOBALNA          816
908      0.000      MOHAWK INDS          908
1071     0.015         PVH CORP         1071
1101     0.001 RESTAURANT GROUP         1101
1357     0.084 TUPPERWARE BRAND         1357
```

Source: Author's elaboration.

Figure A.5: Optimal weights for synthetic control of the company "DEBENHAMS"

```
$tab.v
                     v.weights
R                    0
GP                   0
COGS                 0
EMP                  0.351
KL                   0
GHG                  0
P                    0
RI                   0.045
special.GHG_EMP.2005 0.159
special.GHG_EMP.2006 0.075
special.GHG_EMP.2007 0.185
special.GHG_EMP.2008 0.185
```

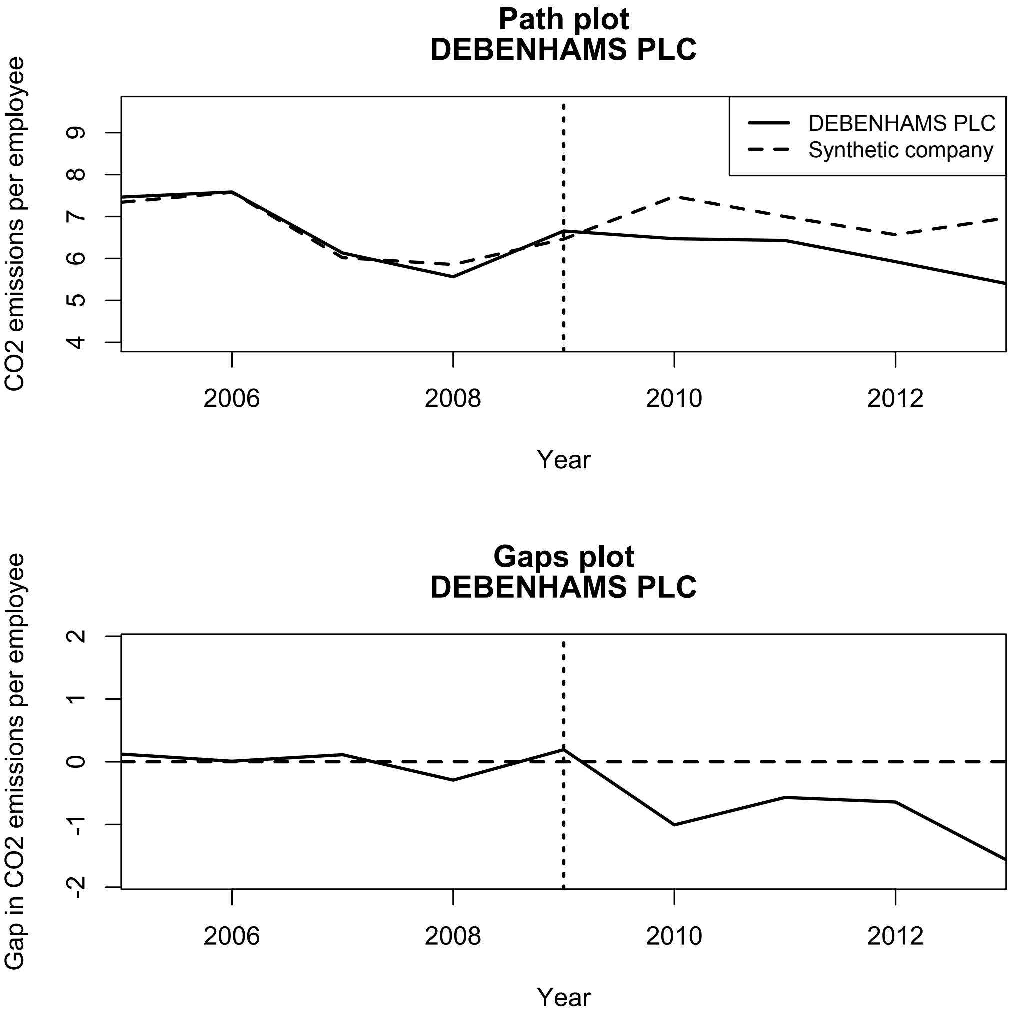
Source: Author's elaboration.

Figure A.6: Predictors' weight for synthetic control of the company "DEBENHAMS"

```
$tab.pred
                      Treated  Synthetic Sample Mean
R                    3937.198  11243.009    9840.471
GP                    678.554   1900.564    2308.367
COGS                 3258.644   9342.444    7532.098
EMP                 25486.500  25461.808   24038.583
KL                  67365.037  47608.478  150835.855
GHG                169126.500 422328.595  529772.146
P                       2.998      5.797      23.716
RI                    159.790    207.718    3312.377
special.GHG_EMP.2005    7.463      7.341      15.127
special.GHG_EMP.2006    7.585      7.577      15.247
special.GHG_EMP.2007    6.131      6.019      14.563
special.GHG_EMP.2008    5.563      5.856      15.190
```

Source: Author's elaboration.

Figure A.7: Treated effects for company "DEBENHAMS"



Source: Author's elaboration.

Figure A.8: Path and gaps plots of the company "DEBENHAMS"

```
# Placebo gaps data

> placebo.data$p.gaps.data

     DEBENHAMS PLC BLOOMSBURY PUBL CHIME COMMUNICAT CINEWORLD GROUP FIAT CHRYSLER AU FUTURE PLC
2005   0.122113871     -0.33512984      -0.03639431      -0.3815492        1.3447303  0.5622978
2006   0.008454128     -0.47886195       0.05727377       0.9695022        0.6068070  0.6274852
2007   0.112171278     -0.02825890       0.06382242       0.2505468        0.6491470 -1.0602120
2008  -0.292961475      0.03281298      -0.09399626      -0.6967589       -2.1600912 -0.5091866
2009   0.193088601     -0.53104800       0.01796652      -2.1931031       -6.4480451  1.0924287
2010  -1.006822614     -0.44126672      -0.02317348      -4.0523202        1.1051677  0.8451190
2011  -0.569185343      0.30961872      -0.71778532      -5.3838476        0.2886103  1.3469621
2012  -0.642107052     -0.06300761      -0.41391257      -3.4817202        1.0201325  1.3928916
2013  -1.563949296      0.17105217      -0.77996239      -4.2087497       -0.9745326  2.3055472
     HARLEYNDAVIDSON HOWDEN JOINERY G LIBERTY GLOBALNA MOHAWK INDS   PVH CORP RESTAURANT GROUP
2005     -0.79894967        0.5692431        0.2752905    32.01991  1.9529418       0.31578787
2006      1.66657408       -1.5961107        0.4004502    30.88229 -0.4065026       0.08040454
2007      0.13773359        1.2040084       -1.6492399    33.42222 -0.4442271      -0.33832431
2008     -0.80014317       -0.1448424        0.8038444    37.62800 -1.2460007      -0.08440156
2009     -0.09466666       -2.9341117       -1.9460788    41.99778 -2.1682149       0.90352103
2010      3.88725178       -7.5758652       -4.3482746    49.41503 -3.2704115      -1.35019130
2011      8.23899475       -5.4681568       -4.4435783    49.01530 -7.7956705      -1.28135540
2012     10.09665081       -4.5172050       -2.3199739    35.68888 -7.8415892      -1.23536835
2013      6.75387436       -7.1411257      -14.3701678    56.58550 -6.9832405      -0.33079648
     TUPPERWARE BRAND
2005       -0.9447216
2006        0.5073607
2007        0.8437779
2008       -0.3512600
2009        0.5136837
2010       -1.1743715
2011       -0.3497365
2012        1.1479265
2013        0.8116233
```

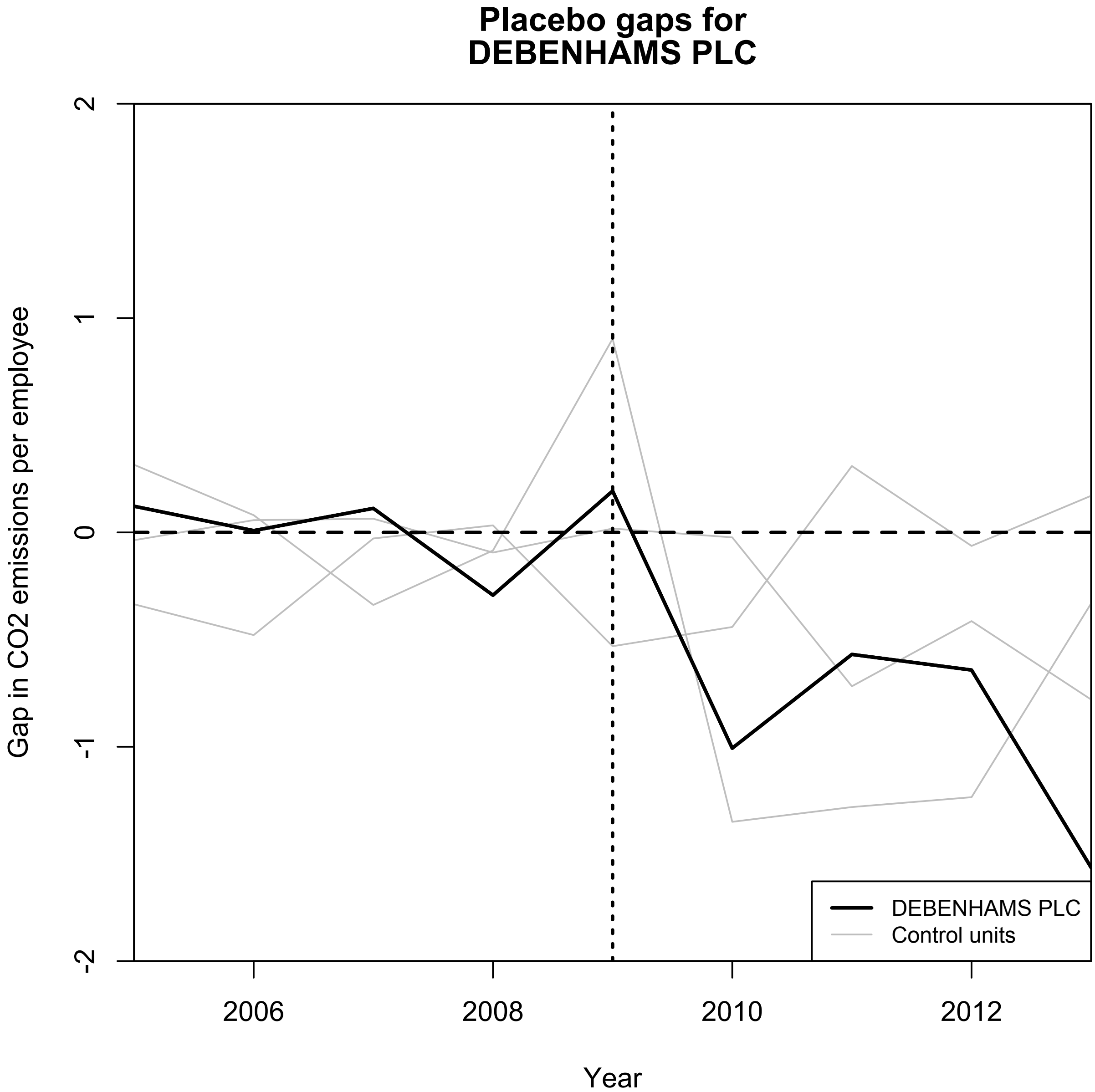
Source: Author’s elaboration.

Figure A.9: In-space placebo treated effects, exemple of the company “DEBENHAMS”

```
# 3.2 MSPE Pre-Treatment, Post-Treatment, MSPE ration

> mse.f(wdf, data = p.gaps.data, unit = tr.id, period = t.p)

$mse.pre
   DEBENHAMS PLC  BLOOMSBURY PUBL CHIME COMMUNICAT  CINEWORLD GROUP FIAT CHRYSLER AU       FUTURE PLC
    2.834802e-02     8.587401e-02     4.378357e-03     4.084403e-01     1.815975e+00     5.233092e-01
 HARLEYNDAVIDSON HOWDEN JOINERY G LIBERTY GLOBALNA      MOHAWK INDS         PVH CORP RESTAURANT GROUP
    1.018747e+00     1.085556e+00     9.005758e-01     1.127975e+03     1.432270e+00     5.694346e-02
TUPPERWARE BRAND
    4.963146e-01

$mse.post
   DEBENHAMS PLC  BLOOMSBURY PUBL CHIME COMMUNICAT  CINEWORLD GROUP FIAT CHRYSLER AU       FUTURE PLC
       0.8466372        0.1211642        0.2591481       16.0105530        8.9744724        2.1955257
 HARLEYNDAVIDSON HOWDEN JOINERY G LIBERTY GLOBALNA      MOHAWK INDS         PVH CORP RESTAURANT GROUP
      46.1115798       33.4608600       50.8648211     2216.7548921       37.2850791        1.1833599
TUPPERWARE BRAND
       0.7483605

$mse.ratio
   DEBENHAMS PLC  BLOOMSBURY PUBL CHIME COMMUNICAT  CINEWORLD GROUP FIAT CHRYSLER AU       FUTURE PLC
       29.865828         1.410953        59.188436        39.199252         4.941958         4.195465
 HARLEYNDAVIDSON HOWDEN JOINERY G LIBERTY GLOBALNA      MOHAWK INDS         PVH CORP RESTAURANT GROUP
       45.263019        30.823717        56.480334         1.965251        26.032151        20.781316
TUPPERWARE BRAND
        1.507835

$rmse.pre
   DEBENHAMS PLC  BLOOMSBURY PUBL CHIME COMMUNICAT  CINEWORLD GROUP FIAT CHRYSLER AU       FUTURE PLC
      0.16836871       0.29304267       0.06616915       0.63909332       1.34758119       0.72340117
 HARLEYNDAVIDSON HOWDEN JOINERY G LIBERTY GLOBALNA      MOHAWK INDS         PVH CORP RESTAURANT GROUP
      1.00933014       1.04190002       0.94898671      33.58534419       1.19677500       0.23862828
TUPPERWARE BRAND
      0.70449599

$rmse.post
   DEBENHAMS PLC  BLOOMSBURY PUBL CHIME COMMUNICAT  CINEWORLD GROUP FIAT CHRYSLER AU       FUTURE PLC
       0.9201289        0.3480864        0.5090659        4.0013189        2.9957424        1.4817306
 HARLEYNDAVIDSON HOWDEN JOINERY G LIBERTY GLOBALNA      MOHAWK INDS         PVH CORP RESTAURANT GROUP
       6.7905508        5.7845363        7.1319577       47.0824266        6.1061509        1.0878235
TUPPERWARE BRAND
       0.8650783

$rmse.ratio
   DEBENHAMS PLC  BLOOMSBURY PUBL CHIME COMMUNICAT  CINEWORLD GROUP FIAT CHRYSLER AU       FUTURE PLC
        5.464964         1.187835         7.693402         6.260931         2.223051         2.048283
 HARLEYNDAVIDSON HOWDEN JOINERY G LIBERTY GLOBALNA      MOHAWK INDS         PVH CORP RESTAURANT GROUP
        6.727780         5.551911         7.515340         1.401874         5.102171         4.558653
TUPPERWARE BRAND
        1.227939

$m.pr.tr.effect
   DEBENHAMS PLC  BLOOMSBURY PUBL CHIME COMMUNICAT  CINEWORLD GROUP FIAT CHRYSLER AU       FUTURE PLC
    -0.012555550     -0.202359428     -0.002323594      0.035435232      0.110148276     -0.094903921
 HARLEYNDAVIDSON HOWDEN JOINERY G LIBERTY GLOBALNA      MOHAWK INDS         PVH CORP RESTAURANT GROUP
     0.051303706      0.008074591     -0.042413701     33.488104199     -0.035947140     -0.006633365
TUPPERWARE BRAND
     0.013789244

$m.tr.effect
   DEBENHAMS PLC  BLOOMSBURY PUBL CHIME COMMUNICAT  CINEWORLD GROUP FIAT CHRYSLER AU       FUTURE PLC
      -0.7177951       -0.1109303       -0.3833734       -3.8639482       -1.0017334        1.3965897
 HARLEYNDAVIDSON HOWDEN JOINERY G LIBERTY GLOBALNA      MOHAWK INDS         PVH CORP RESTAURANT GROUP
       5.7764210       -5.5272929       -5.4856147       46.5405005       -5.6118253       -0.6588381
TUPPERWARE BRAND
       0.1898251
```

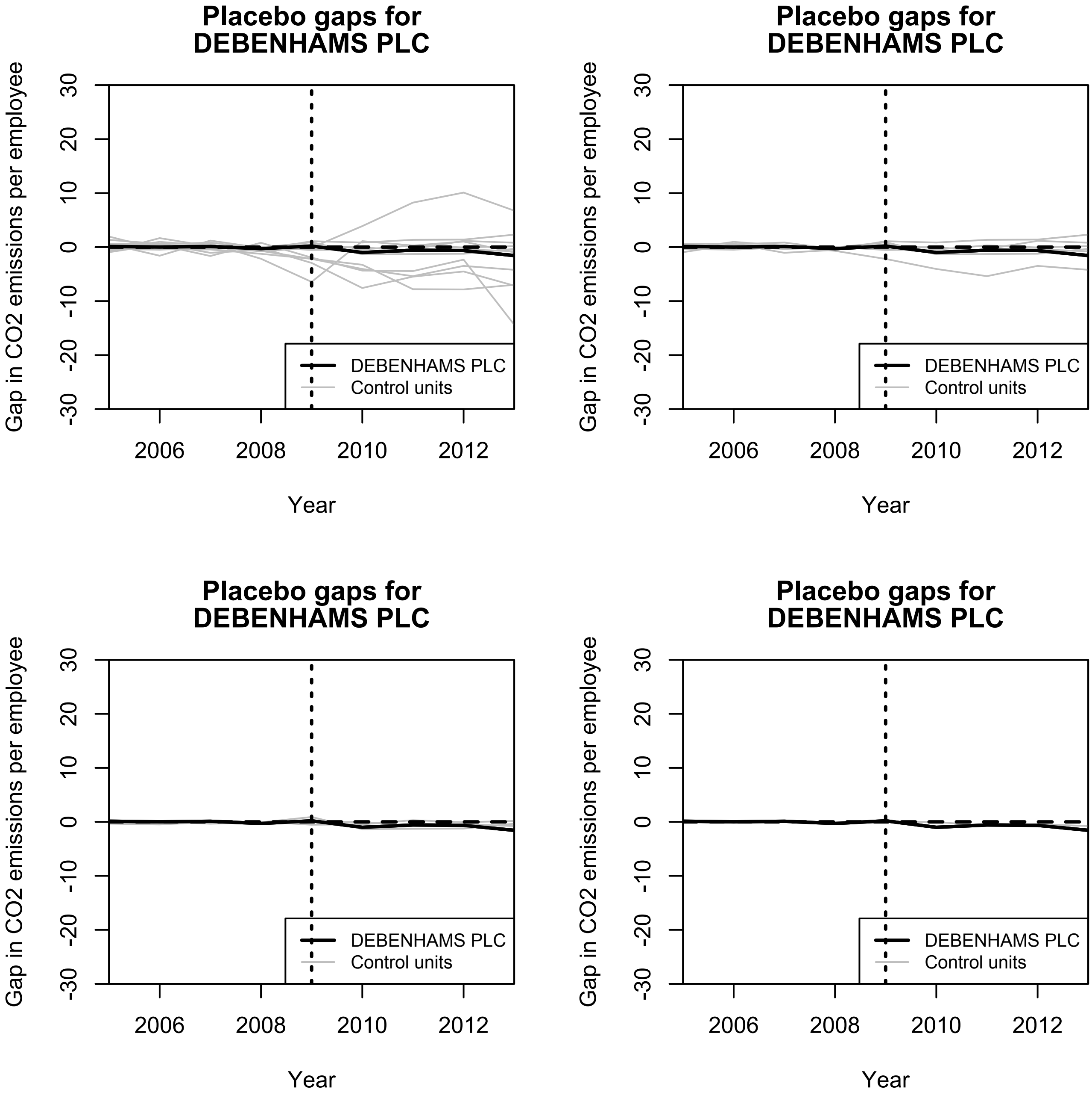
Source: Author's elaboration.

Figure A.10: Root mean squared prediction errors and related statistics in-space placebo, exemple of the company "DEBENHAMS"



Source: Author's elaboration.

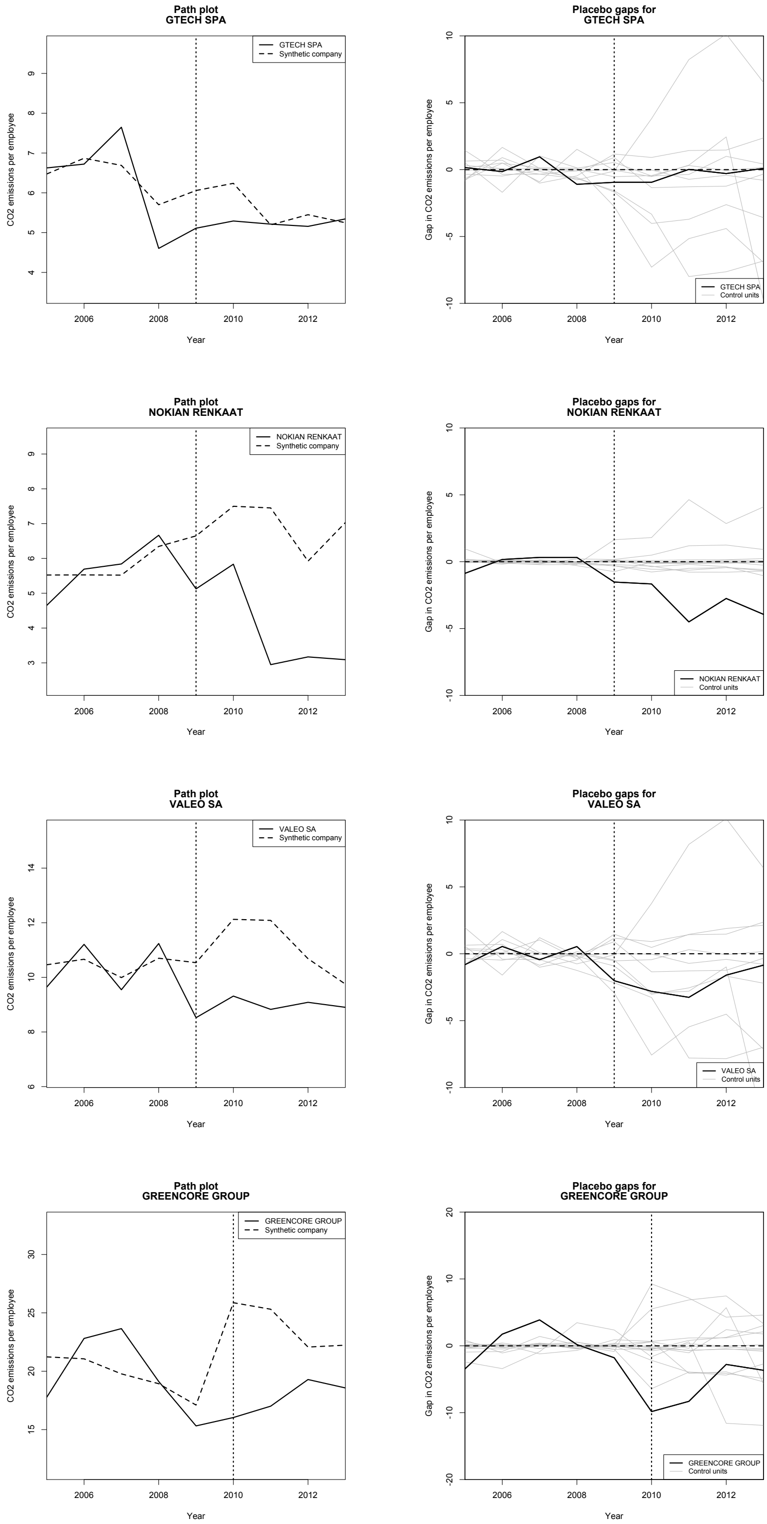
Figure A.11: Placebo plot of the company "DEBENHAMS"



Source: Author's elaboration.

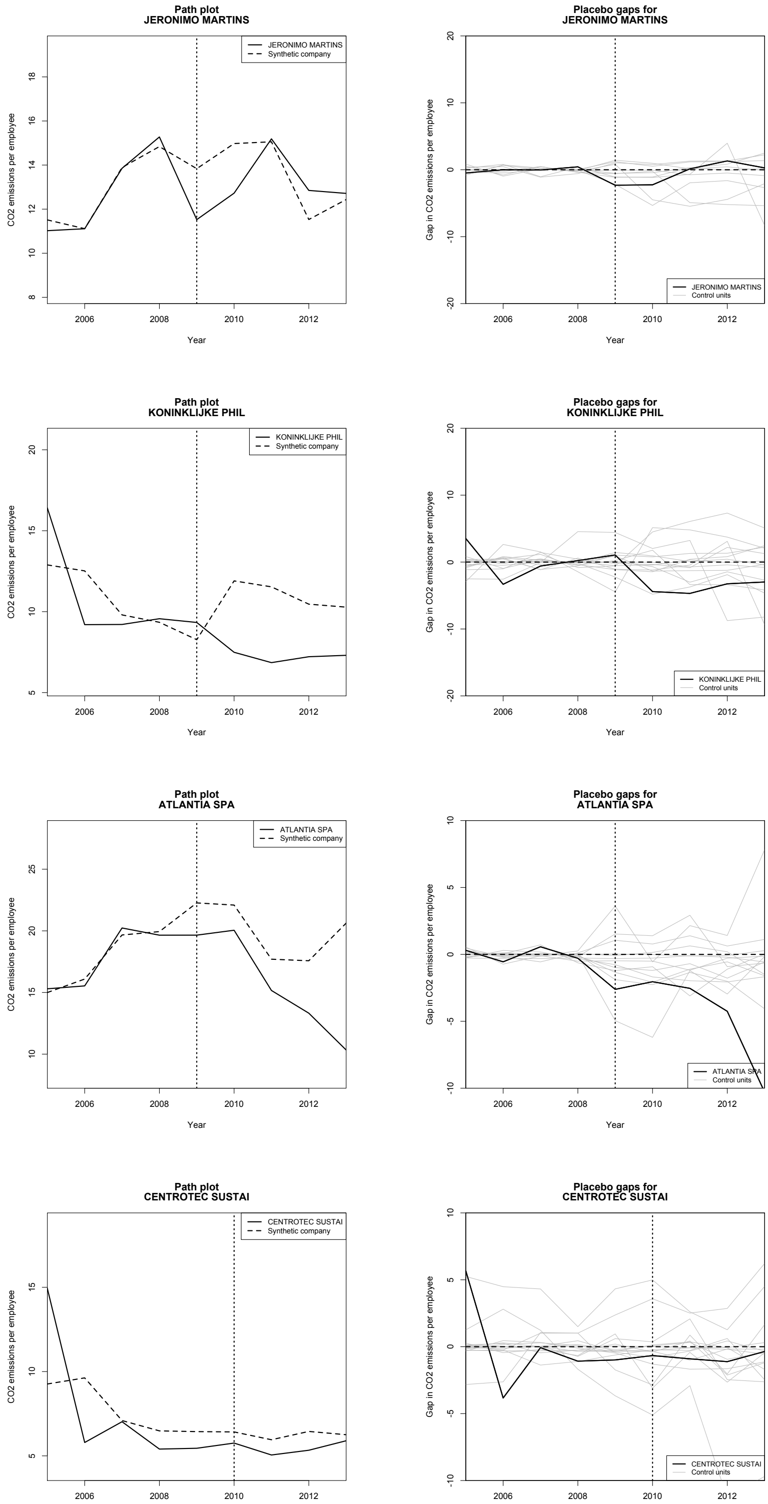
Figure A.12: Placebo plots of the company "DEBENHAMS" (with different root mean squared prediction error exclusion rules)

A.5 Results of the synthetic control analysis



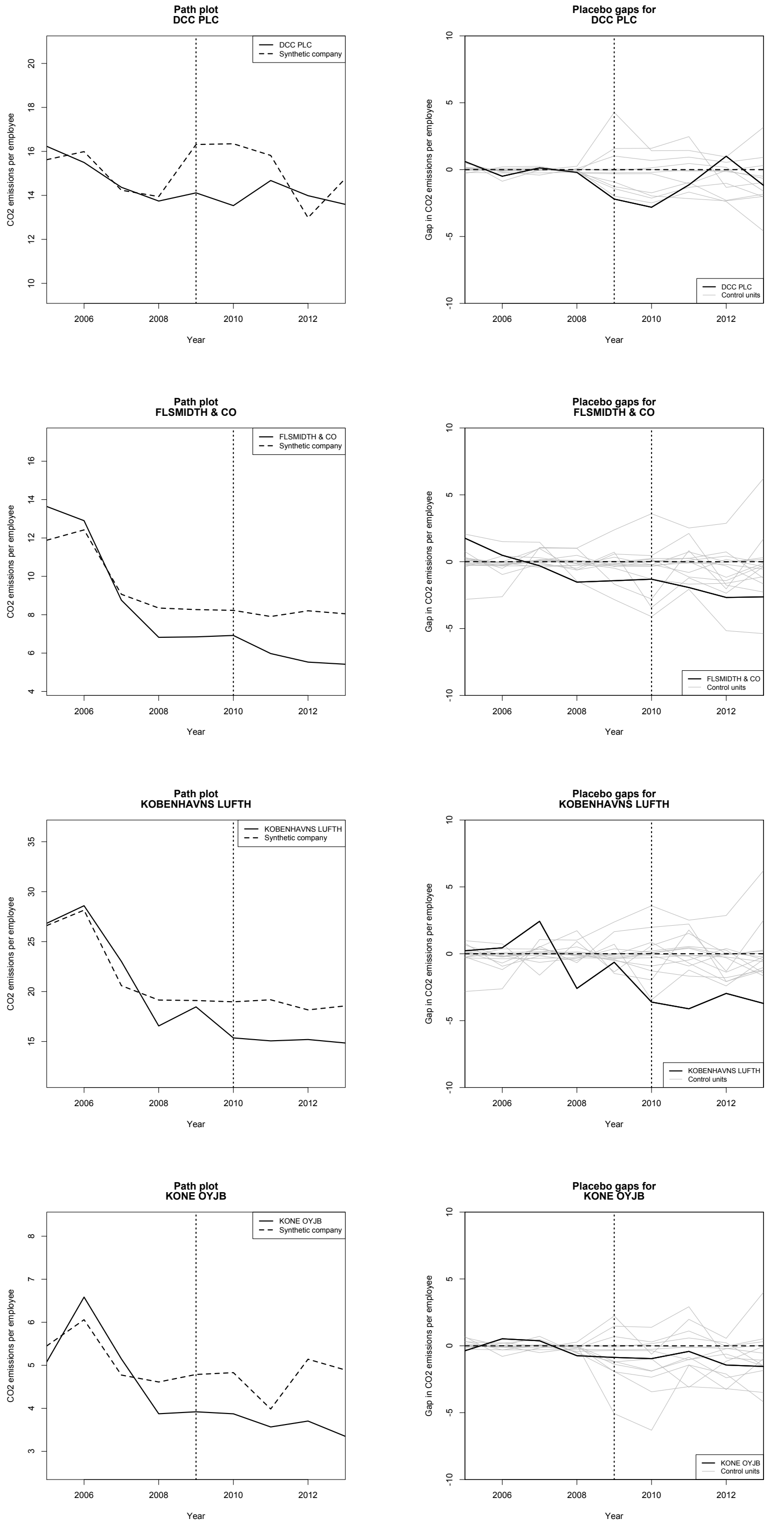
Source: Author's elaboration.

Figure A.13: Synthetic matching and permutation tests Gtech, Nokian, Valeo, Greencore



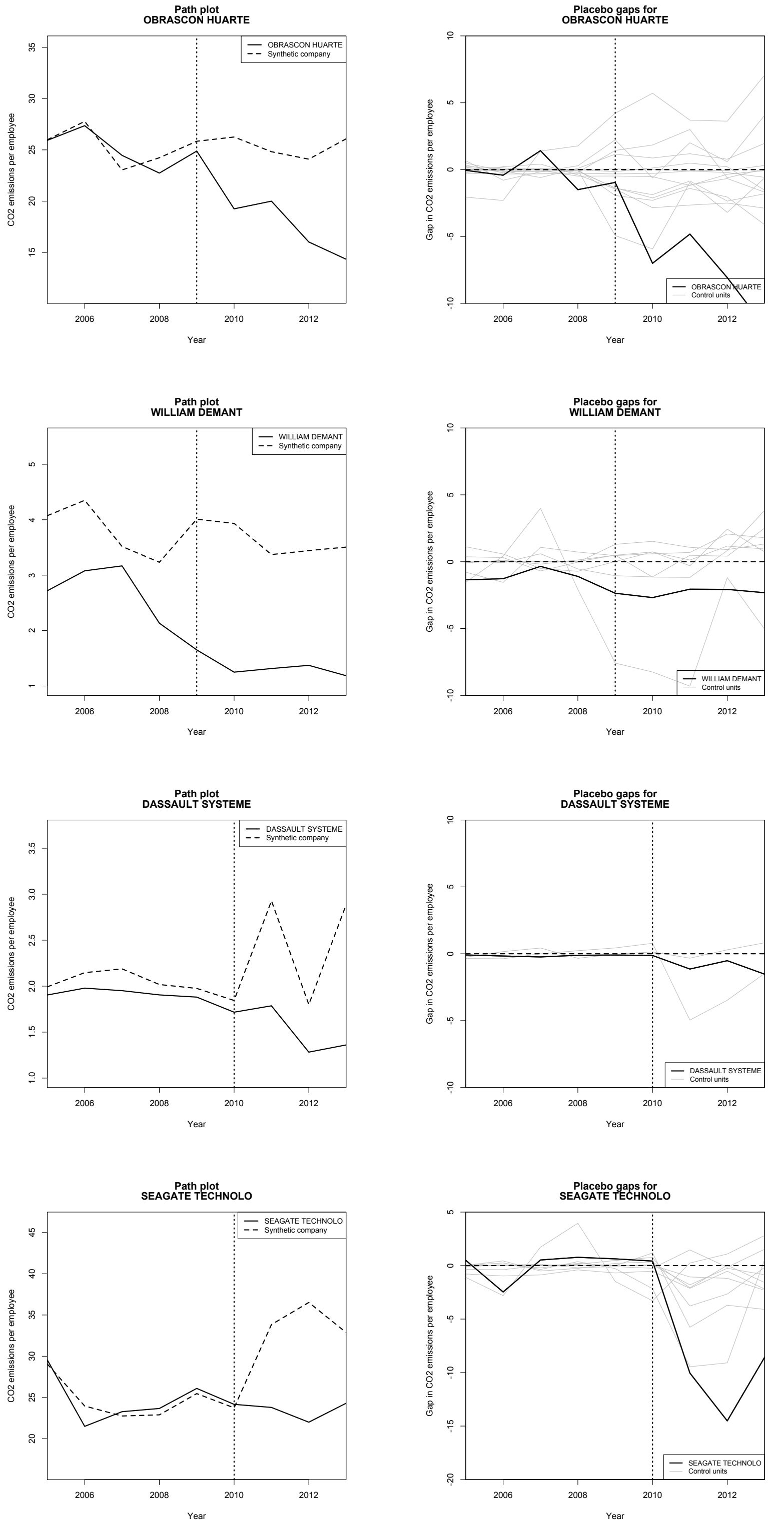
Source: Author's elaboration.

Figure A.14: Synthetic matching and permutation tests Jeronimo, Koninklijke, Atlantia, Centrotec



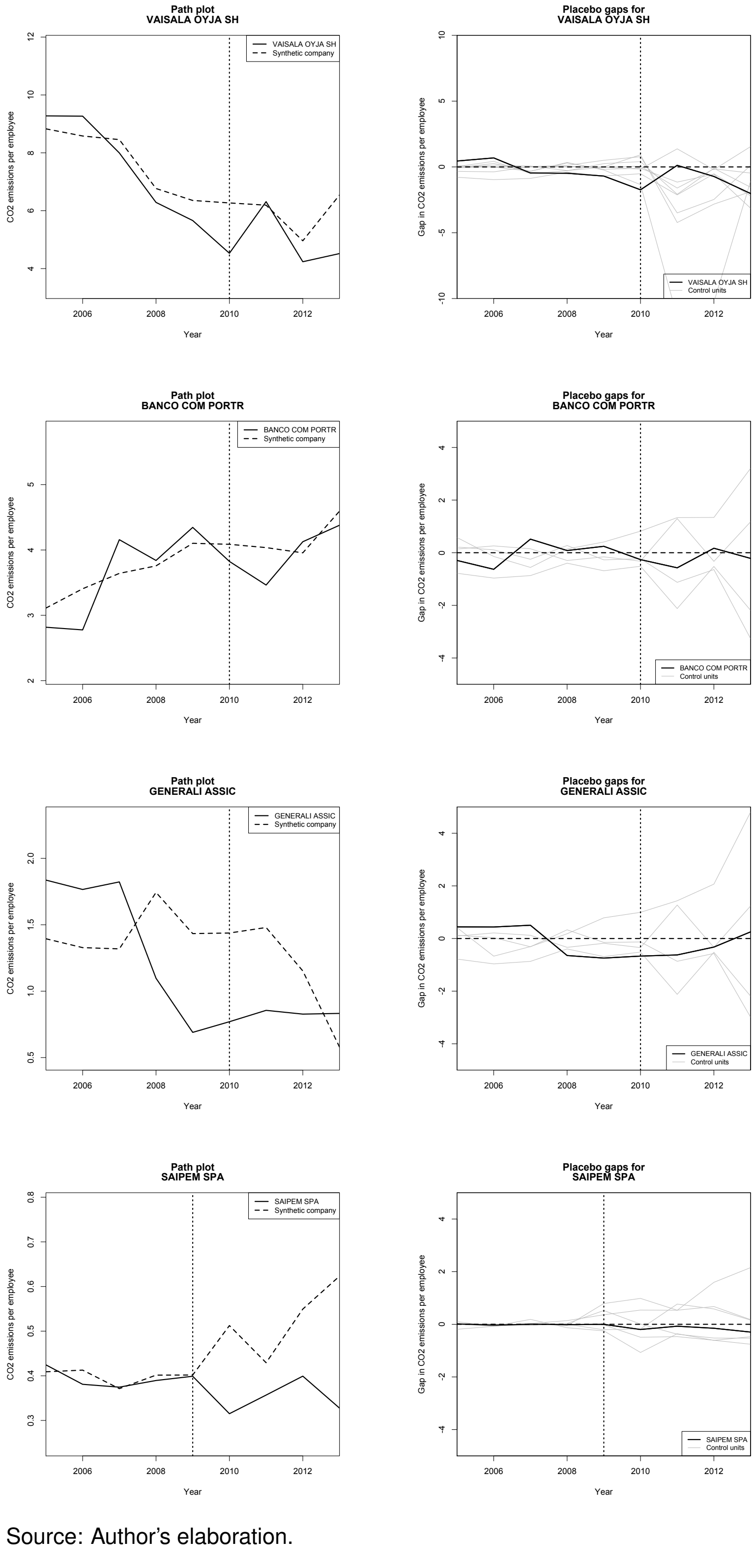
Source: Author’s elaboration.

Figure A.15: Synthetic matching and permutation tests Dcc, FlSmidth, Kobenhavns, Kone



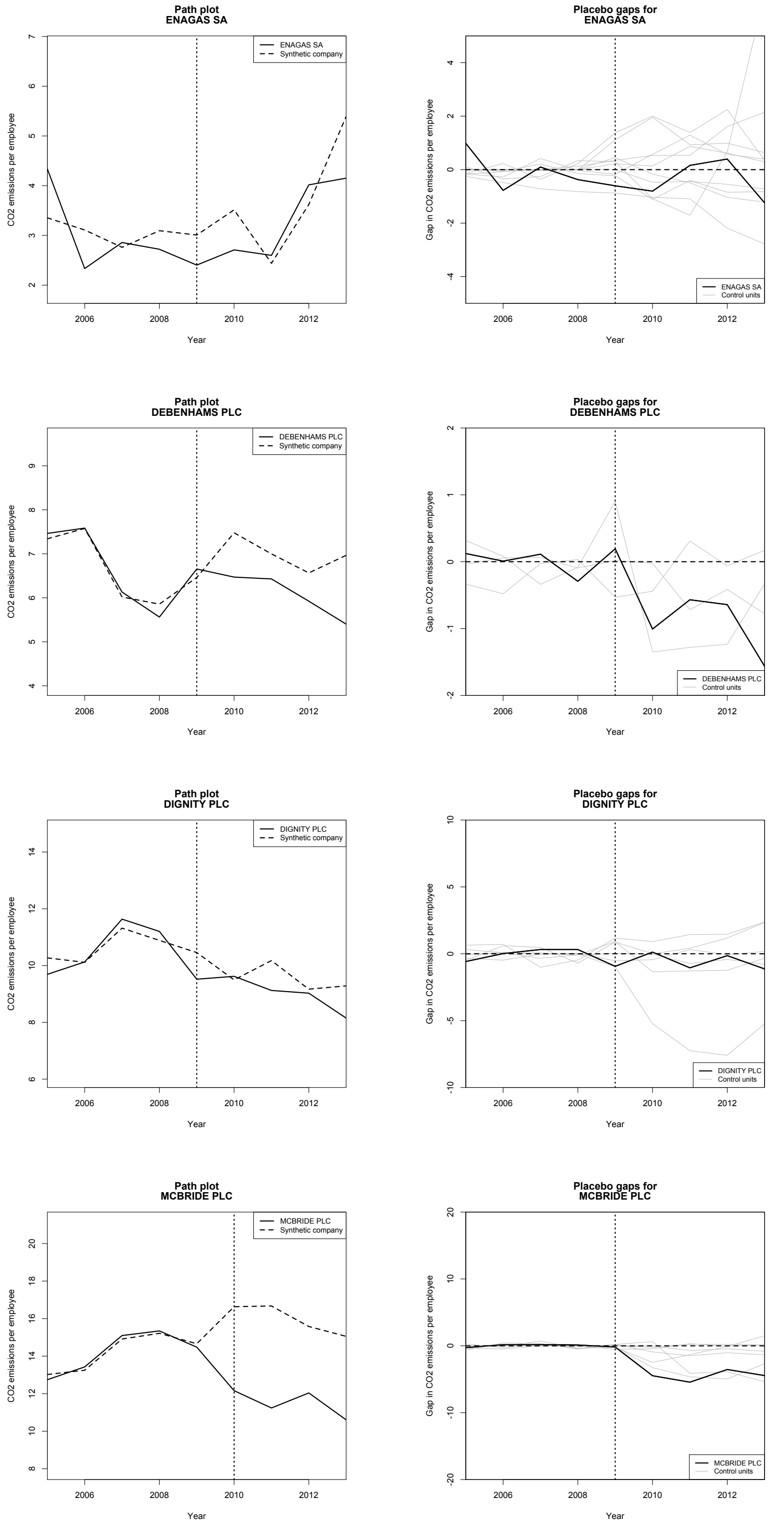
Source: Author's elaboration.

Figure A.16: Synthetic matching and permutation tests Obrascon, William, Dassault, Seagate



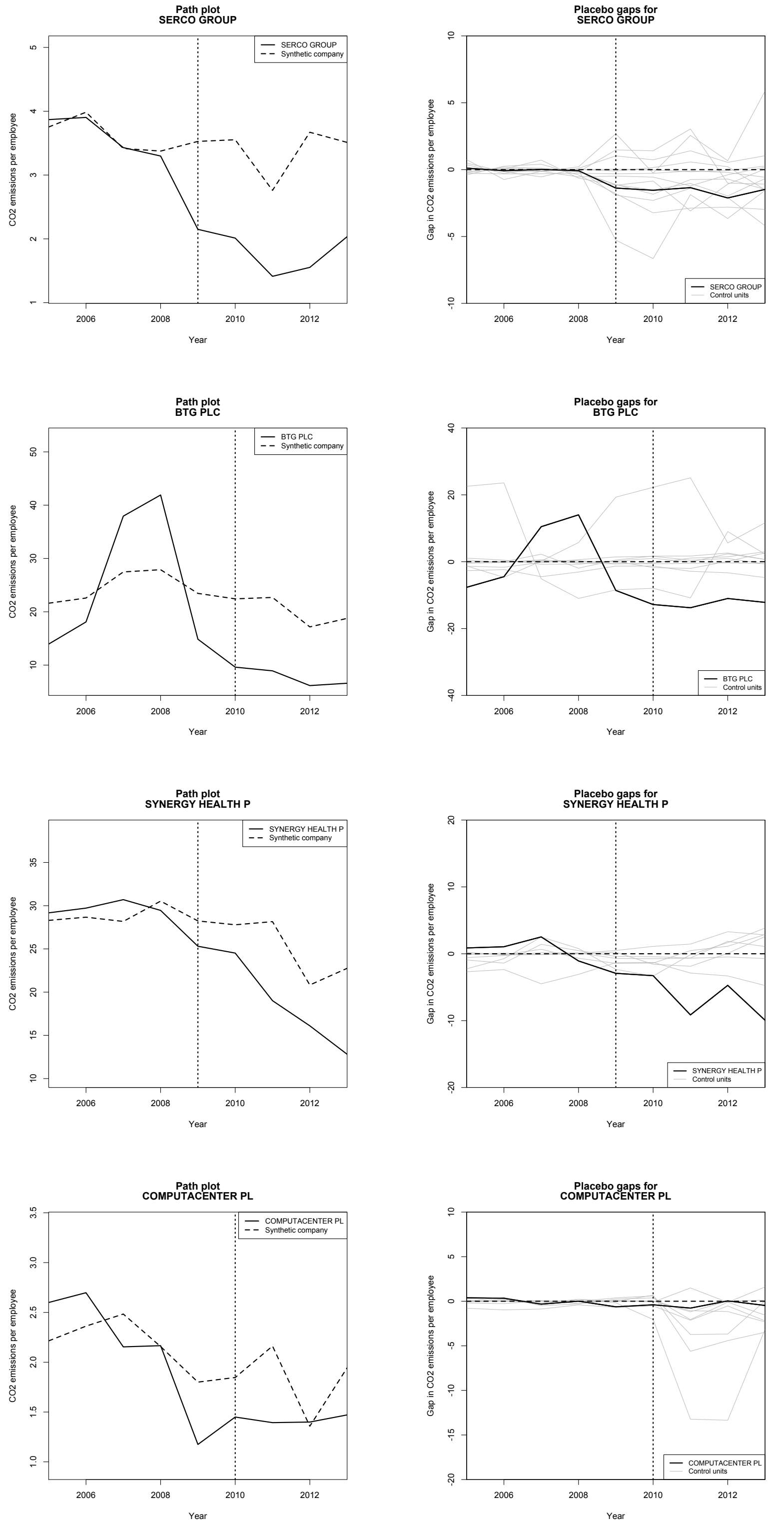
Source: Author's elaboration.

Figure A.17: Synthetic matching and permutation tests Vaisala, Banco, Generali, Saipem



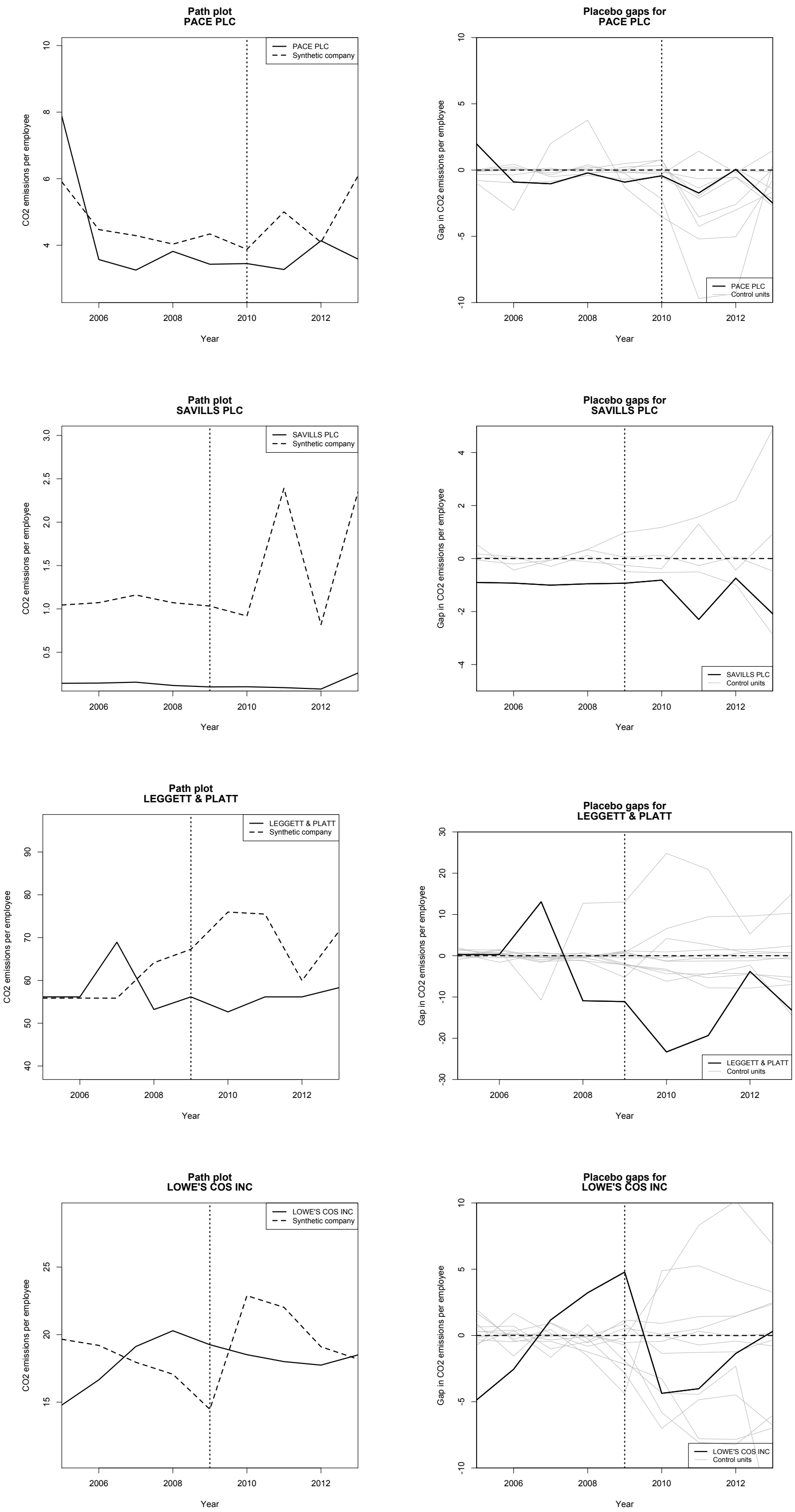
Source: Author's elaboration.

Figure A.18: Synthetic matching and permutation tests Enagas, Debenhams, Dignity, McBride



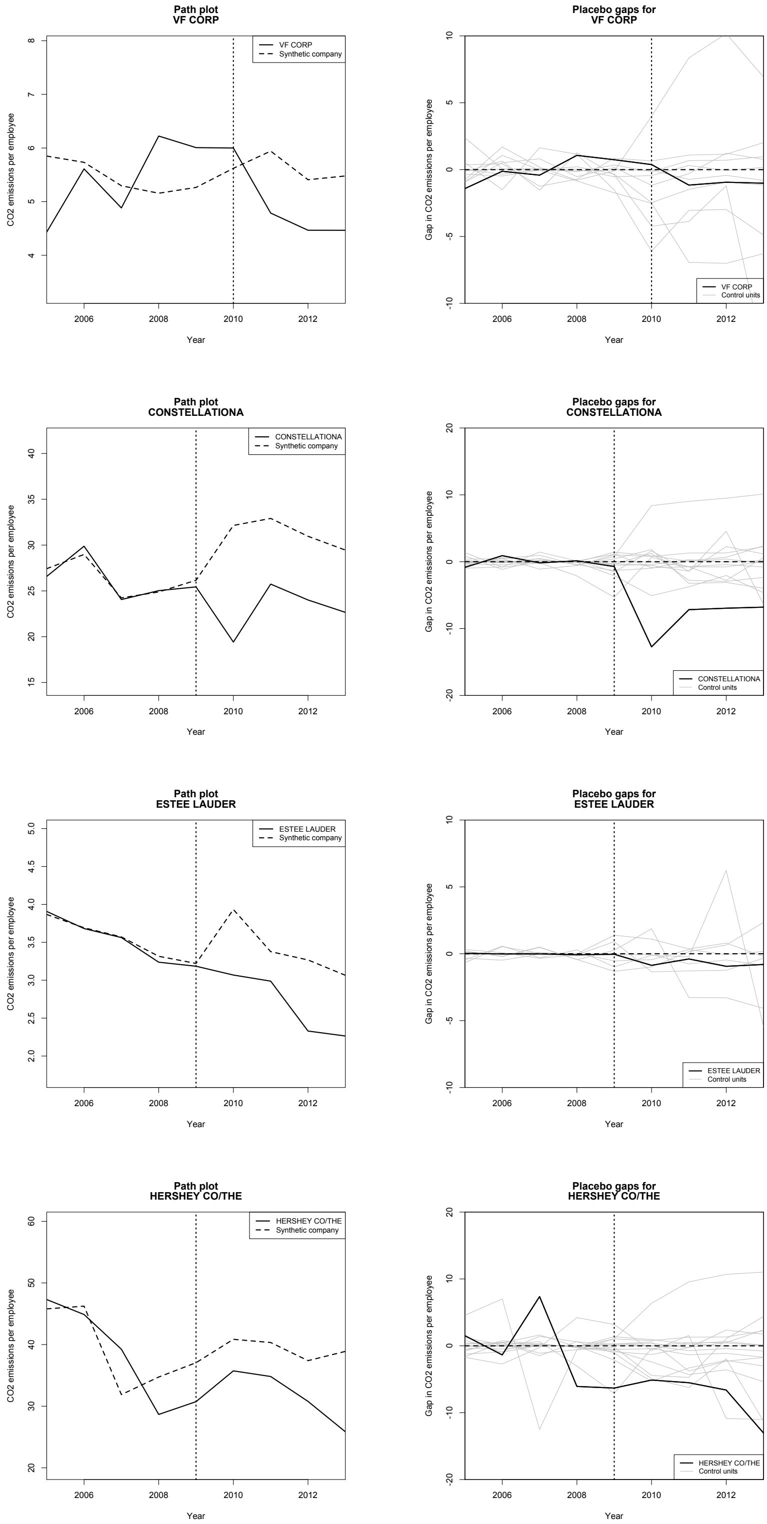
Source: Author’s elaboration.

Figure A.19: Synthetic matching and permutation tests Serco, Btg, Synergy, Computacenter



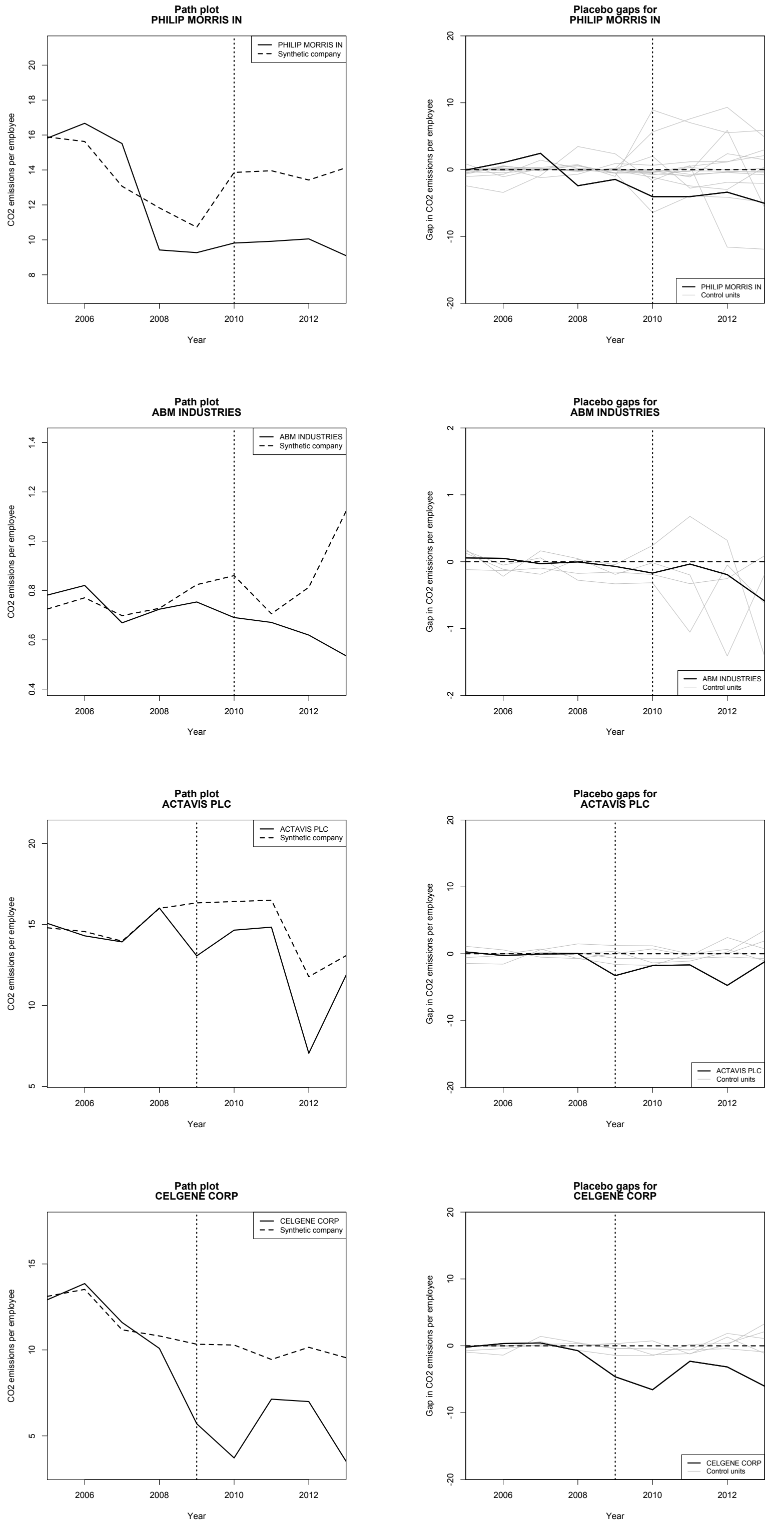
Source: Author's elaboration.

Figure A.20: Synthetic matching and permutation tests Pace, Savills, Leggett, Lowescos



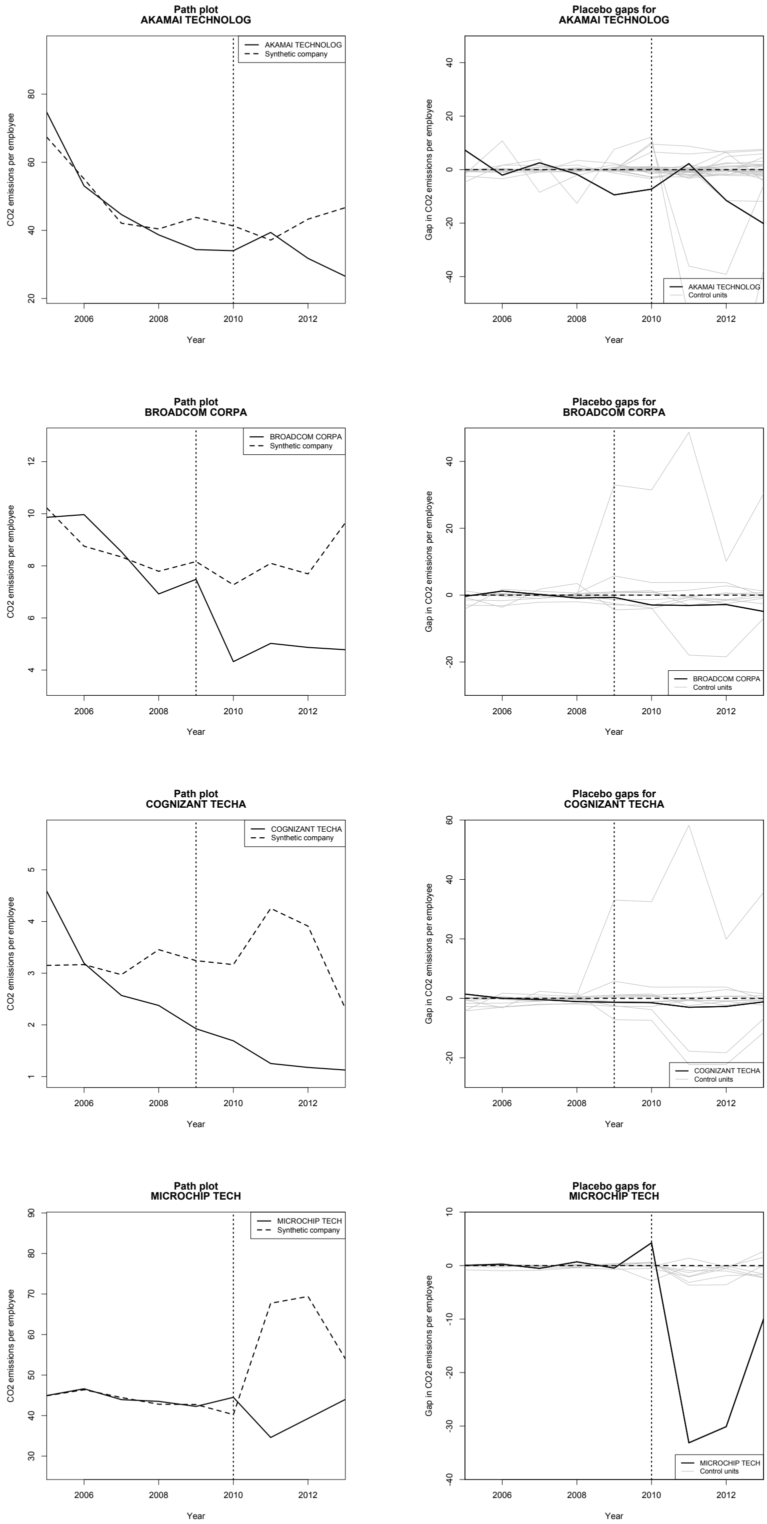
Source: Author's elaboration.

Figure A.21: Synthetic matching and permutation tests VfCorp, Constallationa, EsteeLauder, Hershey



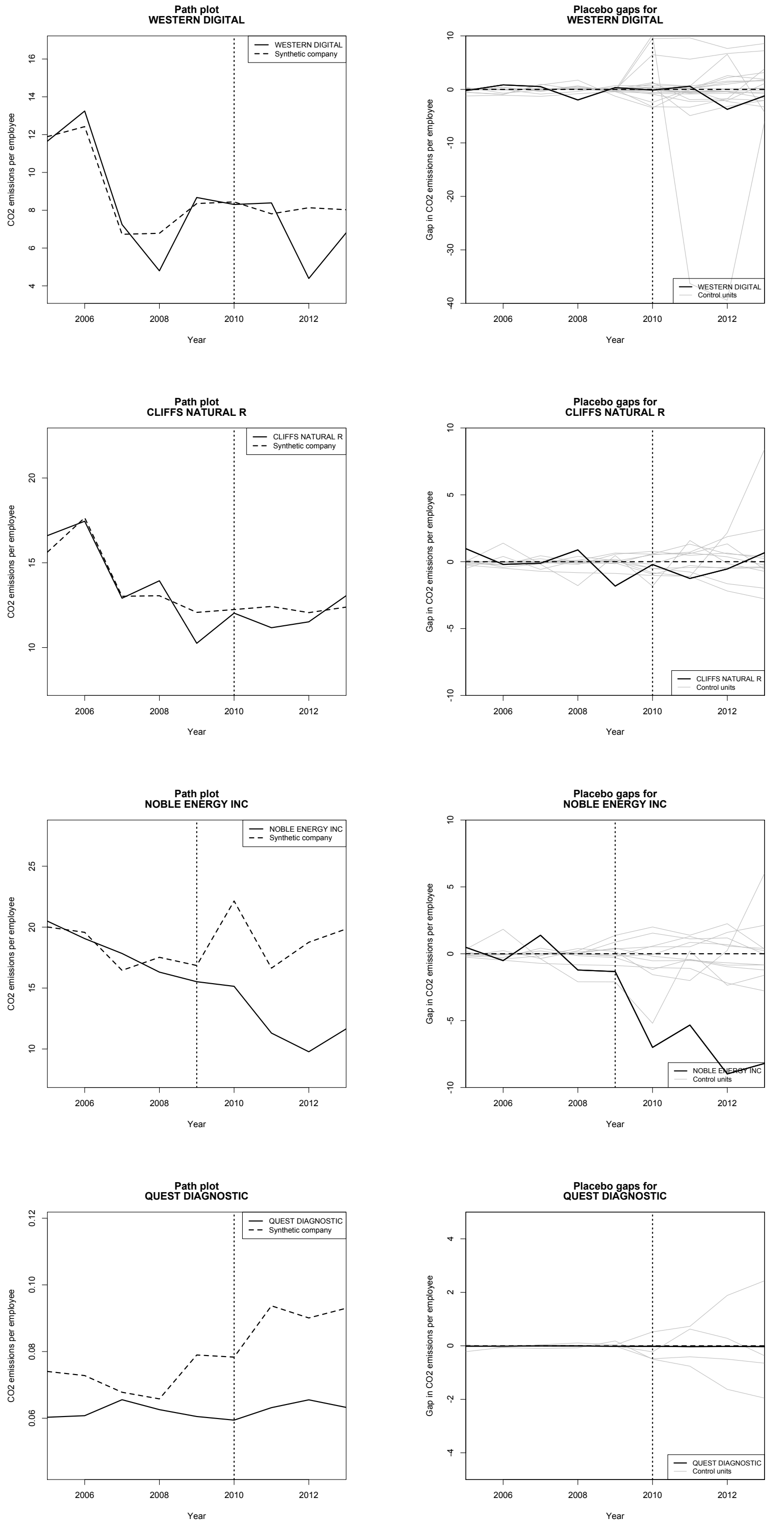
Source: Author's elaboration.

Figure A.22: Synthetic matching and permutation tests Philipmorris, Abm, Actavis, Celgene



Source: Author's elaboration.

Figure A.23: Synthetic matching and permutation tests Akamai, Broadcom, Cognizant, Microhip



Source: Author's elaboration.

Figure A.24: Synthetic matching and permutation tests Western, Cliffs, Noble, Quest

Scripts

```
# ============================================================================
#
#              .oooo.     .oooo.o  .oooo.    ooo. .oo.  .oo.
#             `P  )88b  d88(  "8 `P  )88b  `888P"Y88bP"Y88b
#              .oP"888  `"Y88b.   .oP"888   888   888   888
#             d8(  888  o.  )88b d8(  888   888   888   888
#             `Y888""8o 8""888P' `Y888""8o o888o o888o o888o
#
#
#                   Applied Statistics and Modelling
#                       Department of Informatics
#                  University of Fribourg (Switzerland)
#
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#
#  PROJECT:
#
#     PhD Thesis   Synthetic Control Approach   Library
#
#  PROGRAMME:
#
#     Mylib.r
#
#  OBJECTIVE:
#
#     Fonctions ad hoc:
#
#
# ============================================================================
#
# sp.pr.f                        SPECIAL PREDICTORS
#
# ============================================================================
#
# DESCRIPTION
#
# The function sp.pr.f creates a list of the special predictors to be used
# in the function dataprep()
#
# USAGE

sp.pr.f <- function(moddata, unit = tr.id, yr1 = 2005, yr2 = 2005, yr3 = 2008,
                    yr4 = 2009, val1 = 1, val2 = 2, v2 = "GHG_EMP", stat =
                    "mean"){

  # ARGUMENTS
  #
  # moddata : Data that contains the unit of interest
  # unit    : Unit number, by default treatment identifier tr.id
  # v2      : Variable to be generated, eg. "GHG_EMP"
  # stat    : Statistic to be generated, eg. "mean"
  # yr1     : 1st value of the the first year vector
  # yr2     : 1st value of the the second year vector
  # yr3     : Last value of the the first year vector
```

```
  # yr4      : Last value of the the second year vector
  # val1     : Value of the filter variable, by default set to 1
  # val2     : Value of the filter variable, by default set to 2
  #
  # VALUES
  #
  # time     : Values to be generated. One or more unit of times as
  #            vector, e.g. 2005:2009. Depending on he treatment year. By
  #            default we specified that the first year is 2005 and the last
  #            2008 or 2009
  # sp.pr    : List of the special predictors, eg.
  #                                  list(list("GHG_EMP", 2005, "mean"),
  #                                       list("GHG_EMP", 2006, "mean"),
  #                                       list("GHG_EMP", 2007, "mean"),
  #                                       list("GHG_EMP", 2008, "mean")
  #                                       )

  time ← year.vec.f(moddata, unit, yr1, yr2, yr3, yr4)

  sp.pr ← vector("list", length(time))

  for(i in 1:length(time)){

    sp.pr[[i]] ← list(v2, time[i], stat)

  }

  return(sp.pr)
}


# ============================================================================
#
# year.vec.f                    YEAR VECTOR
#
# ============================================================================
#
# DESCRIPTION
#
# The function year.vec.f creates a vector that define the time vector that
# is specific to the treatment variable w.r.t the treatment year
#
# USAGE

year.vec.f ← function(moddata, unit = tr.id, yr1,
                      yr2, yr3, yr4, v1 = "CDP", val1 = 1, val2 = 2){

  # ARGUMENTS
  #
  # moddata : Data that contains the unit of interest
  # unit     : Unit number, by default treatment identifier tr.id
  # v1       : Filter variable that specify the treatment year
  # yr1      : 1st value of the the first year vector
  # yr2      : 1st value of the the second year vector
  # yr3      : Last value of the the first year vector
  # yr4      : Last value of the the second year vector
  # val1     : Value of the filter variable, by default set to 1
  # val2     : Value of the filter variable, by default set to 2
  #
  # VALUES
  #
  # year.vec : Values to be generated. One or more unit of times as vector,
  #             e.g. 2005:2009, or also just a scalar 2008:2008. Depending on
  #             the treatment variable and needed year
  #
```

```
  # NOTE
  #
  #         This function is mostly used to specify the time or year vectors
  #         to be used as arguments in different functions. In our case, we
  #         define by default val1 and val2 equal to 1 (treated in 2009),
  #         2 (treated in 2009)

  if(unique(moddata[is.element(moddata$ID2, unit), v1]) == val1)
    {year.vec <- c(yr1:yr3)}
  if(unique(moddata[is.element(moddata$ID2, unit), v1]) == val2)
    {year.vec <- c(yr2:yr4)}

  return(year.vec)
}


# ==============================================================================
#
# unit.par.f                PARAMETRES OF THE UNIT
#
# ==============================================================================
#
# DESCRIPTION
#
# The function unit.par.f gives the values of the parameters for the
# unit of interest
#
# USAGE

unit.par.f <- function(moddata, unit = tr.id, v3 = "NAME"){

  # ARGUMENTS
  #
  # moddata : Data that contains the unit of interest
  # unit    : Unit number, by default treatment identifier tr.id
  # v3      : The variable that gives us the value to be found
  #
  # VALUES
  #
  # unit.par: Values to be generated, e.g. the name of the company
  #
  # NOTE
  #
  #           This function is mostly used to specify the name of the company
  #           as an argument in other functions

  unit.par <- unique(moddata[is.element(moddata$ID2, unit), v3])

  return(unit.par)
}


# ==============================================================================
#
# dataprep.arg                   DATAPREP ARGUMENTS
#
# ==============================================================================
#
# DESCRIPTION
#
# The function dataprep.arg creates a list of arguments to be used in the
# function dataprep
#
# USAGE
```

```
dataprep.arg ← function(){

  # VALUES
  #
  # mypar : List of arguments to be used
  #
  # NOTE
  #
  #         This function doesn't contains any arguments as itself it
  #         creates a list of arguments. Before we can implement the
  #         function dataprep, all the arguments has to be specified in the
  #         environment

  mypar1 ← alist(predictors = pr,
                 predictors.op = pr.op,
                 dependent = dep,
                 unit.variable = u.v,
                 time.variable = t.v,
                 special.predictors = sp.pr,
                 time.predictors.prior = t.pr.p,
                 time.optimize.ssr = t.op.ssr,
                 unit.names.variable = u.n.v,
                 time.plot = t.p)

  mypar2 ← alist(treatment.identifier = tr.id,
                 controls.identifier = c.id)

  mypar ← c(alist(foo = data.frame(wdf)), mypar1, mypar2)

  return(mypar)
}


# ============================================================================
#
# gaps.f                              GAPS
#
# ============================================================================
#
# DESCRIPTION
#
# The function gaps.f calculates the gaps of the output variable between the
# treated unit and its synthetic control
#
# USAGE

gaps.f ← function(dataprep.out, synth.out){

  # ARGUMENTS
  #
  # dataprep.out : Output of the function dataprep
  # synth.out    : Output of the function synth
  # Y1plot       : Values of the output variable of the treated unit
  # Y1plot       : Values of the output variable of the control unit
  # solution.w   : Values of the w weights
  #
  # VALUES
  #
  # gaps: The period by period discrepancies between the treated unit and
  #       its synthetic control unit
  #
  # NOTE
  #
  #       The output from synth can be flexibly combined with the output
  #       from dataprep to compute other quantities of interest. In order to
```

```
  #       get this values, we need to have first the synth output

  gaps ← dataprep.out$Y1plot    (dataprep.out$Y0plot %*% synth.out$solution.w)

  return(gaps)
}

# ===========================================================================
#
# path.plot.f                   PATH PLOTS
#
# ===========================================================================
#
# DESCRIPTION
#
# The function gaps.plot.f gives summary "path" plots
#
# USAGE

path.plot.f ← function(moddata, unit = tr.id, yr1 = 2009, yr2 = 2010,
                        yr3 = 2009, yr4 = 2010, dataprep.out, synth.out){

  # ARGUMENTS
  #
  # moddata       : Data that contains the unit of interest
  # unit          : Unit number, by default it is treatment identifier tr.id
  # yr1           : 1st value of the the first year vector
  # yr2           : 1st value of the the second year vector
  # yr3           : Last value of the the first year vector
  # yr4           : Last value of the the second year vector
  # dataprep.out  : Output of the function dataprep
  # synth.out     : Output of the function synth
  #
  # VALUES
  #
  # path.plot: Gives the summary plots for outcome trajectories of the treated
  #            and the synthetic control unit
  #
  # NOTE
  #
  #            We use the functions tr.year to set the treatment year, and
  #            tr.name to set the treatment unit name. For more informations
  #            see function path.plot or gaps.plot. The labels are already
  #            set. For the tr.year we want to have only a scalar equal to
  #            2009 or 2009, that's why we put as values  yr1 = 2008,
  #            yr2 = 2009, yr3 = 2008, yr4 = 2009


  tr.year ← year.vec.f(moddata, unit, yr1, yr2, yr3, yr4)

  tr.name ← unit.par.f(moddata, unit)

  path.plot ← path.plot(synth.res = synth.out, dataprep.res = dataprep.out,
              tr.intake = tr.year,
              Ylab = c("CO2 emissions per employee"),
              Xlab = c("Year"),
              Legend = c(tr.name, "Synthetic company"),
              Main = c("Path plot", tr.name)
              )
}


# ===========================================================================
#
# gaps.plot.f                   GAPS PLOTS
```

```
#
# ============================================================================
#
# DESCRIPTION
#
# The function gaps.plot.f gives summary "gaps" plots
#
# USAGE

gaps.plot.f ← function(moddata, unit = tr.id, yr1 = 2009, yr2 = 2010,
                       yr3 = 2009, yr4 = 2010, dataprep.out, synth.out){

  # ARGUMENTS
  #
  # moddata      : Data that contains the unit of interest
  # plot         : Defined which plot we want. Either gaps.plt ("gaps"), or
  #                path.plot ("path")
  # unit         : Unit number, by default it is treatment identifier tr.id
  # yr1          : 1st value of the the first year vector
  # yr2          : 1st value of the the second year vector
  # yr3          : Last value of the the first year vector
  # yr4          : Last value of the the second year vector
  # dataprep.out : Output of the function dataprep
  # synth.out    : Output of the function synth
  #
  # VALUES
  #
  # gaps.plot: Gives the summary plots for outcome trajectories gaps of the
  #            treated and the synthetic control (treated   synthetic)
  #
  # NOTE
  #
  #           We use the functions tr.year to set the treatment year, and
  #           tr.name to set the treatment unit name. For more informations
  #           see function path.plot or gaps.plot. The labels are already
  #           set. For the tr.year we want to have only a scalar equal to
  #           2009 or 2009, that's why we put as values  yr1 = 2008,
  #           yr2 = 2009, yr3 = 2008, yr4 = 2009


  tr.year ← year.vec.f(moddata, unit, yr1, yr2, yr3, yr4)

  tr.name ← unit.par.f(moddata, unit)

  gaps.plot ← gaps.plot(synth.res = synth.out, dataprep.res = dataprep.out,
             tr.intake = tr.year,
             Ylab = c("Gap in CO2 emissions per employee"),
             Xlab = c("Year"),
             Main = c("Gaps plot", tr.name)
             )
}


# ============================================================================
#
# p.vec.par.f               PLACEBO VECTOR OF PARAMETRES
#
# ============================================================================
#
# DESCRIPTION
#
# The function p.vec.par.f gives the vector of values of the parameters for
# the unit of interest, which will be used in the placebo tests
#
# USAGE
```

```
p.vec.par.f ← function(moddata, unit_1 = tr.id, unit_2 = c.id,
                        v4 = "NAME"){

  # ARGUMENTS
  #
  # moddata : Data that contains the unit of interest
  # unit_1  : Unit number of the treated unit, by default it is the
  #           treatment identifier tr.id
  # unit_2  : Unit number of the control units, by default it is the control
  #           identifier tr.id
  # v4      : The parameter that gives us the value to be found
  #
  # VALUES
  #
  # p.vec.par : Values to be generated, e.g. the name of the companies
  #
  # NOTE
  #
  #           This function is mostly used to specify the names or id's of
  #           the treated and control companies for the placebo tests
  #           company as an argument in other functions



  p.vec.par ← c(unit.par.f(moddata, unit = unit_1, v4),
                unit.par.f(moddata, unit = unit_2, v4))

  return(p.vec.par)
}


# ============================================================================
#
# placebo.data.f                    PLACEBO DATA
#
# ============================================================================
#
# DESCRIPTION
#
# The function placebo.data.f produce the placebo data, as placebo gaps and
# placebo
#
# USAGE

placebo.data.f ← function(moddata, p.vec.name, p.vec.id, period = t.p){

  # ARGUMENTS
  #
  # moddata    : Data that contains the unit of interest
  # period     : Time plot value, eg. t.p ← 2005:2013
  # p.vec.name : Vectors of the names of "placebo" treated units
  # p.vec.id   : Vectors of the id numbers of "placebo" treated units
  #
  #
  # VALUES
  #
  # p.gaps.data  : Is the matrix that stores the values of the gaps of all the
  #                "placebo" treated units
  # p.synth.tab  : Gives a list of the synth.tables for all "placebo" treated
  #                units
  # dataprep.out : Prepare the data for the function synth, see also
  #                dataprep.arg function
  # synth.out    : Gives the result of the synthetic control methods, see
  #                also the function synth
```

```
#
# NOTE
#
#        This function produce the matrix of the placebo gaps and
#        synth.tabes for all the treated ann control units. In order to get
#        the results, the function formals(dataprep) ← dataprep.arg() has
#        to be already run before

# Create the "store" matrix and snyth.table.list vector

store                  ← matrix(NA, length(period), length(p.vec.name))
colnames(store)        ← p.vec.name

p.synth.tab.list       ← vector(mode = "list", length(p.vec.name))
names(p.synth.tab.list) ← p.vec.name

# Run the bug

for(i in 1:length(p.vec.name)){

    # Redefine tr.id, c.id in the mypar object (see dataprep.arg), to take the
    # values from the global environment

      tr.id  <<- p.vec.id[i]
      c.id   <<- p.vec.id[ i]

    # Run synth

      dataprep.out  ← dataprep()

      synth.out     ← synth(dataprep.out)

      synth.tables  ← synth.tab(dataprep.res = dataprep.out,
                                synth.res = synth.out)

    # Store gaps and synth.tables

    store[,i]           ← gaps.f(dataprep.out, synth.out)

    p.synth.tab.list[i] ← list(synth.tables)
}

# Get the data

data            ← store
rownames(data) ← period

# Get the p.synth.tab

p.synth.tab ← p.synth.tab.list

# Redefine the value of the tr.id in the global environment

tr.id <<- p.vec.id[1]

return(list(p.gaps.data = data, p.synth.tab = p.synth.tab))
}


# ============================================================================
#
# mse.f                              MSPE
#
# ============================================================================
#
```

```
# DESCRIPTION
#
# The function mse.f creates a list of different mean squared prediction error
# (MSPE)
#
# USAGE

mse.f ← function(moddata, data = p.gaps.data, unit = tr.id, period = t.p,
                 pyr1 = 2008, pyr2 = 2009, pyr3 = 2008, pyr4 = 2009,
                 tyr1 = 2009, tyr2 = 2010, tyr3 = 2009, tyr4 = 2010){

  # ARGUMENTS
  #
  # moddata : Data that contains the unit of interest
  # data    : The matrix containing the data of "placebo" gaps for all
  #           "placebo" tested units, see function gap.test.data.f
  # unit    : Unit number, by default treatment identifier tr.id
  # period  : Time plot value, by default t.p ← 2005:2013
  # pyr     : Pre treatment year, for more see year.vec.f function
  # tyr     : Treatment year, for more see year.vec.f function
  #
  # VALUES
  #
  # pr.year         : Last pre treatment year
  # tr.year         : Treatment year
  # gap.end.pre     : Gives the last pretreatment year and it's position in the
  #                   vector
  # treat.start     : Gives the last pretreatment year and it's position in the
  #                   vector
  # mse.pre         : Vector of the pretreatment MSPE
  # mse.post        : Vector of the post treatment MSPE (including the treatment
  #                   year)
  # mse.ratio       : Vector of the MSPE ratios (mse.post/mse.pre)
  # rmse.pre        : Vector of the pretreatment RMSPE
  # rmse.post       : Vector of the post treatment RMSPE (including the treatment
  #                   year)
  # rmse.ratio      : Vector of the RMSPE ratios (mse.post/mse.pre)
  # m.tr.effect     : Average treatment effect over all treatment years
  # m.pr.tr.effect  : Average pre treatment effect over all pre treatment years
  # company.mse     : True treated company MSPE

  # NOTE
  #         This function gives us the list of different MSPE. They will be
  #          used to do more placebo analyses

  # Set bounds in gaps data

  gap.start     ← 1
  gap.end       ← length(period)
  pr.year       ← year.vec.f(moddata, unit, yr1 = pyr1, yr2 = pyr2, yr3 = pyr3,
                             yr4 = pyr4)
  tr.year       ← year.vec.f(moddata, unit, yr1 = tyr1, yr2 = tyr2, yr3 = tyr3,
                             yr4 = tyr4)
  gap.end.pre   ← which(rownames(data) == pr.year)
  treat.start   ← which(rownames(data) == tr.year)

  # Get different MSPE

  mse.pre       ← apply(data[gap.start:gap.end.pre,]^2, 2, mean)
  mse.post      ← apply(data[treat.start:gap.end,]^2, 2, mean)
  mse.ratio     ← (mse.post)/(mse.pre)
  rmse.pre      ← (mse.pre)^0.5
  rmse.post     ← (mse.post)^0.5
  rmse.ratio    ← (mse.post)^0.5/(mse.pre)^0.5
  m.tr.effect   ← apply(data[treat.start:gap.end,], 2, mean)
```

```
  m.pr.tr.effect ← apply(data[gap.start:gap.end.pre,], 2, mean)
  company.mse    ← as.numeric(mse.pre[1])


  return(list(mse.pre = mse.pre, mse.post = mse.post, mse.ratio=mse.ratio,
  rmse.pre = rmse.pre, rmse.post = rmse.post, rmse.ratio = rmse.ratio,
  m.pr.tr.effect = m.pr.tr.effect, m.tr.effect = m.tr.effect, company.mse =
  company.mse))
}


# ============================================================================
#
# p.synth.plot.f          PLACEBO SYNTH PLOT
#
# ============================================================================
#
# DESCRIPTION
#
# The function p.synth.plot.f gives summary gaps plot, that represent the "true"
# treated unit and the "placebo" (control) treated unites

# USAGE

p.synth.plot.f ← function(moddata, mse, x, data = p.gaps.data,
                          unit = tr.id, period = t.p, c1, c2, pyr1 = 2008,
                          pyr2 = 2009, pyr3 = 2008, pyr4 = 2009, tyr1 = 2009,
                          tyr2 = 2010, tyr3 = 2009, tyr4 = 2010){

  # ARGUMENTS
  #
  # moddata : Data that contains the unit of interest
  # mse     : Values of the function mse.f
  # x       : Values to be excluded from the gap.test.data,
  #           usualy x ← 5*mse$company.mse
  # data    : The matrix containing the data of "placebo" gaps and synth.tables
  #           for all  "placebo" tested units, see function gap.test.data.f
  # unit    : Unit number, by default treatment identifier tr.id
  # period  : Time plot value, by default t.p ← 2005:2013
  # c1      : First value that determines the  y length of the graph (eg.  10)
  # c2      : Second value that determines the y length of the graph (eg. 10)
  # pyr     : Pre treatment year, for more see year.vec.f function
  # tyr     : Treatment year, for more see year.vec.f function
  #
  # VALUES
  #
  # pr.year       : Last pre treatment year
  # tr.year       : Treatment year
  # gap.end.pre   : Gives the last pretreatment year and it's position in the
  #                 vector
  # treat.start   : Gives the last pretreatment year and it's position in the
  #                 vector
  # tr.name       : Name of the treated unit
  # data.plot     : New data, containing the excluded values, see argument x
  # plot          : Gives the placebo effect figure with all the units
  #
  # NOTE
  #            This function needs the specific c1 and c2 values for each unit


  # Set bounds in gaps data

  gap.start    ← 1
  gap.end      ← length(period)
  pr.year      ← year.vec.f(moddata, unit, yr1 = pyr1, yr2 = pyr2, yr3 = pyr3,
```

```
                               yr4 = pyr4)
  tr.year         ← year.vec.f(moddata, unit, yr1 = tyr1, yr2 = tyr2, yr3 = tyr3,
                               yr4 = tyr4)
  gap.end.pre     ← which(rownames(data) == pr.year)
  treat.start     ← which(rownames(data) == tr.year)

  # Set treated name and year

  tr.name ← unit.par.f(moddata, unit)

  # Exclude companies with x times higher MSPE than the treated

  data.plot ← data[,mse$mse.pre < x]
  Cex.set ← .75

  # Plot

  plot(period, data.plot[gap.start:gap.end,
              which(colnames(data.plot) == tr.name)],
      ylim = c(c1,c2), # to be defined CASE BY CASE
      xlab = "Year",
      xlim = c(period[1], period[length(period)]),
      ylab = "Gap in CO2 emissions per employee",
      main = c("Placebo gaps for", tr.name),
      type = "l", lwd = 2, col = "black",
      xaxs = "i", yaxs = "i")

      # Add lines for control states

        for (i in 1:ncol(data.plot)){

             lines(period, data.plot[gap.start:gap.end, i], col="gray")
        }

     # Add treated company line

        lines(period, data.plot[gap.start:gap.end,
             which(colnames(data.plot) == tr.name)],
             lwd = 2, col = "black")

     # Add grid

        abline(v = tr.year, lty = "dotted", lwd = 2)
        abline(h = 0, lty = "dashed", lwd = 2)
        legend("bottomright", legend = c(tr.name, "Control units"),
               lty = c(1,1), col = c("black","gray"), lwd=c(2,1), cex=.8)
        # arrows(1967, 1.5, 1968.5, 1.5, col = "black", length=.1)
        # text(1961.5, 1.5, "Terrorism Onset", cex=Cex.set)
        abline(v = period[1])
        abline(v = period[length(period)])
        abline(h = c1) # to be defined CASE BY CASE
        abline(h = c2)  # to be defined CASE BY CASE
}
```

Script B.1: My library

```
# =============================================================================
#
#              .oooo.     .oooo.o  .oooo.   ooo. .oo.  .oo.
#             `P  )88b  d88(  "8 `P  )88b  `888P"Y88bP"Y88b
#              .oP"888  `"Y88b.   .oP"888   888   888   888
#             d8(  888  o.  )88b d8(  888   888   888   888
#             `Y888""8o 8""888P' `Y888""8o o888o o888o o888o
#
#
#                   Applied Statistics and Modelling
#                       Department of Informatics
#                  University of Fribourg (Switzerland)
#
#
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#
#  PROJECT:
#
#     PhD Thesis   Synthetic Control Approach
#
#  DATE:
#
#     April 2016
#
#  PROGRAMME:
#
#     Synth_CD.r
#
#  OBJECTIVE:
#
#     Apply synthetic control method to the CD Industry, model dep <- GHG_EMP
#
#  DATA:
#
#     Type          : Qualitative and quantitative data
#
#     Files         : Panel_Companies_Data_New.csv
#
#     N. obs.       : 1215 (135 units)
#
#     N. variables  : 23
#
#     N. periods    : Dataset contains information from 2005   2013 (9 periods)
#
#     Title         : Synthetic Control Method Application
#
#     Source        : Personal work, Package 'Synth' (2015),
#                     Synth: An R Package for Synthetic Control Methods (2011)
#
#     Description   : Data base containing divers variables used for the
#                     analyses
#
#     Variables:
#
#     ID2            : Company identification number (digital);
```

```
#      YEAR              : Year (digital);
#      NAME              : Company short name (nominal);
#      CDP               : Is the company reporting to the CDP
#                          (0: not reporting, 1: in 2009; 2: in 2010) (digital);
#      COUNTRY           : Headquarter (nominal);
#      SECTOR            : Sector (nominal);
#      INDUSTRY_SECTOR   : Industry (nominal);
#      SUB_INDUSTRY      : Subindustry (nominal);
#      CLIMAT_CDP        : Is the company reporting to the Climate change program
#                          (0: No; 1: Yes) (binomial);
#      WATER_CDP         : Is the company reporting to the Water program
#                          (0: No; 1: Yes) (binomial);
#      SUPPLY_CHAIN_CDP: Is the company reporting to the Supply chain program
#                          To identify the year the company started to report,
#                          rem if 1 on 2005 = reported in 2003, 2004 or 2005
#                          (0: No; 1: Yes) (binomial);
#      FOREST_CDP        : Is the company reporting to the Forest program
#                          To identify the year the company started to report,
#                          rem. if 1 on 2005 = reported in 2003, 2004 or 2005
#                          (0: No; 1: Yes) (binomial);
#      GHG               : Company's CO2 emissions in metric tons (digital)
#      S                 : Source of the reported company's greenhouse gas or CO2
#                          emissions (nominal)
#      R                 : Company's revenue in mio (digital)
#      GP                : Company's gross profit in mio (digital)
#      COGS              : Company's cost of goods sold in mio (digital)
#      FA                : Company's fixed assets in mio (digital)
#      EMP               : Company's number of employees (digital)
#      P                 : Company's share price (digital)
#      RI                : Company's return on investment (digital)
#      KL                : Company's capital labor ratio (digital)
#      GHG_EMP           : Company's CO2 emissions in mt per employee (digital)
#
#  REFERENCES:
#
#      Hainmueller, J. and Diamond, A. (2014) Package 'Synth'.
#
#      Abadie, A. and Gardeazabal, J. (2003) Economic Costs of Conflict: A Case
#      Study of the Basque Country American Economic Review 93 (1) 113 132.
#
#      Abadie, A., Diamond, A., Hainmueller, J. (2011). Synth: An R Package for
#      Synthetic Control Methods in Comparative Case Studies. Journal of
#      Statistical Software 42 (13) 1 17.
#
#      Wyncoll, A., The effect of firms reporting to the Carbon disclosure
#      project on their CO2 emissions. An empirical study based on the synthetic
#      control approach.
#
#  COMMENTS:
#
#  REMARKS: Abadie and Gardeazabal (2003) use 13 predictors variables for each
#           region, the variables are: 1964   1969 averages for gross total
#           investment (invest); 1964 1969 schooling variables; 1961 1969
#           average for six industrial sector shares as a percentage of total
#           production; 1960 1969 averages for real GDP per capita ; 1969
#           population density.
#
#
# ===========================================================================

# Initialisation
# ==============

# Chemins d'accès aux dossiers de données
```

```
ddpath  ← "/Volumes/Directories/TurkovaA/My Documents/PhD Thesis/Data/"

# Chemins d'accès aux dossiers de travail

wdpath  ← "/Volumes/Directories/TurkovaA/My Documents/PhD Thesis/Data/"

# Chemins d'accès à mes fonctions ad hoc

jdpath ← "/Volumes/Directories/TurkovaA/My Documents/PhD Thesis/jobs/"

# Fixe le dossier de travail et de données

setwd(wdpath)

# My librairies
# =============

source(file(paste(jdpath, "Mylib.r", sep=""), encoding="latin1"))

# Librairies
# ==========

library(Synth)        # use synthetic control method

library(Hmisc)        # contents, desc ribe, label, summarize

# Remarques Snyth: The synth command identifies optimal weights. The
#                  optimisation method may be ("Nelder Mead', 'BFGS', 'CG',
#                  'L BFGS B','nlm', 'nlminb', 'spg', and 'ucminf"), the default
#                   method is c("Nelder Mead", "BFGS")

# ==============================================================================
#
#                                   Data
#
# ==============================================================================

# 1.1 Data
# ========

# Groupe of treated (Participating 2009/2010) and controls (Non Participating)

wdf ← read.csv2(file(paste(ddpath, "Panel_Companies_Data_New.csv", sep=""),
                encoding="latin1"), header=T, sep=",", dec=".",
                na.strings="NA")

head(wdf)

# 1.2 Data Preparations
# =====================

# 1.2.1 Transform the variable NAME from factor to character

wdf$NAME ← as.character(wdf$NAME)

# 1.2.2 General values of the arguments to be used in dataprep()

# Predictors

pr ←  c("R", "GP", "COGS", "EMP", "KL", "GHG", "P", "RI")

# Predictors.op

pr.op ← "mean"
```

```
# Dependent

dep ← "GHG_EMP"

# Unit.variable

u.v ← "ID2"

# Time.variable

t.v ← "YEAR"

# unit.names.variable

u.n.v ← "NAME"

# time.plot

t.p ← 2005:2013

# ==========================================================================
#
#                              1. CD ob. 403
#
# ==========================================================================

# CD sector observation:
# Year: 2009
# Comments: We have good pre treatment fit and little positive treatment effect.
# The p value is 5/13 for rmse.ratio and the total p value is 4/13 :) In the
# placebo graphs the average p value is 0.4822 compare to 0.244 (best p value).
# ob. 908 is an extreme value.

# 1. Create matrices from panel data that provide inputs for synth()
# ================================================================

# 1.1 Specific values of the arguments to be used in dataprep()

# Treatment identifier

tr.id ← 403

# Controls identifier

c.id ← c(218, 308, 321, 517, 548, 612, 649, 816, 908, 1071, 1101, 1357)

# Special.predictors

sp.pr ← sp.pr.f(wdf, unit = tr.id, v2 = "GHG_EMP", stat = "mean")

# time.predictors.prior

t.pr.p ← year.vec.f(wdf, unit = tr.id, yr1 = 2005, yr2 = 2005, yr3 = 2008,
                    yr4 = 2009)

# time.optimize.ssr

t.op.ssr ← t.pr.p

# 1.2 Run dataprep to prepare the arguments for the function synth

formals(dataprep) ← dataprep.arg()

dataprep.out_403 ← dataprep()
```

```
# 2. Run the synthetic control analyses
# ====================================

# 2.1. Run the synth command to identify optimal weights (see Remarque Synth)

synth.out_403 ← synth(dataprep.out_403)

# 2.2 Compute the gaps

gaps ← gaps.f(dataprep.out_403, synth.out_403)

print(gaps)

# 2.3 Summarise results

# 2.3.1 Summary tables

synth.tables ← synth.tab(dataprep.res = dataprep.out_403, synth.res =
                          synth.out_403)

print(synth.tables)

# 2.3.2 Path plot and gaps plot

op ← par(mfrow = c(2,1))

path.plot ← path.plot.f(wdf, unit = tr.id, yr1 = 2009, yr2 = 2010, yr3 = 2009,
                         yr4 = 2010, dataprep.out_403, synth.out_403)

gaps.plot ← gaps.plot.f(wdf, unit = tr.id, yr1 = 2009, yr2 = 2010, yr3 = 2009,
                         yr4 = 2010, dataprep.out_403, synth.out_403)

par(op)


# 3. Gaps Test
# ============

# Vectors of id's and names

p.vec.name     ← p.vec.par.f(wdf, v4 = "NAME")
p.vec.id       ← p.vec.par.f(wdf, v4 = "ID2")

# 3.1.1 Vector of gaps and synth.tables

# Placebo data

placebo.data_403 ← placebo.data.f(wdf, p.vec.name, p.vec.id, period = t.p)

# Placebo gaps data

p.gaps.data ← placebo.data_403$p.gaps.data

# Placebo synth.tables

p.synth.tab ← placebo.data_403$p.synth.tab

# 3.2 MSPE Pre Treatment, Post Treatment, MSPE ration

mse_403 ← mse.f(wdf, data = p.gaps.data, unit = tr.id, period = t.p)

# 3.3 Figure
```

```
# Values to be excluded from the gap.test.data, usualy x ← 5*mse$company.mse

x ← 5*mse_403$company.mse

# Plot

p.synth.plot.f(wdf, mse_403, x, data = p.gaps.data, unit = tr.id, period = t.p,
               c1 = 2, c2 = 2)
```

Script B.2: Synthetic control analysis customer discretionary sector

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