THE IMPACT OF THE TŌHOKU EARTHQUAKE ON GREENHOUSE GAS EMISSION OF JAPAN: A SYNTHETIC CONTROL METHOD STUDY

A Thesis

by

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ABSTRACT

The synthetic control method (SCM) has been used to assess the impact of a natural disaster, conflict, and political change. The SCM shows an efficient and clear approach for selecting control units based on similarity and provides statistical inference by conducting placebo studies. The SCM is an analytical tool comparing the treated unit with the non-treated unit. The non-treated unit (hereinafter the donor pool) is the group with similar characteristics of the treated unit. Only difference between the two groups is the experience of the treatment (hereinafter the intervention).

The Tōhoku earthquake which occurred in March 2011 is the analysis' intervention. I selected Japan as a treated unit and the donor pool was consisted of 37 countries from the Organization for Economic Co-operation and Development (OECD) and the United Nations Framework Convention on Climate Change (UNFCCC). The outcome variable is Greenhouse Gas (GHG) emission per capita and the intervention window is 1995-2014 (pre-intervention: 1995-2010 and post-intervention: 2011-2014).

The results indicate a positive movement in GHG emission as a result of the earthquake. Placebo studies, leave-one-out tests, and the ratio between post to pre-intervention mean squared prediction error (MSPE), are performed to evaluate the statistical inferences of the analysis. All the tests provide robust evidence and statistical significance of the results. Regardless of the existence of nuclear power facilities in the donor pool, the graphical results almost provide the same direction in the GHG emission.

ACKNOWLEDGEMENTS

The synthetic control method is an efficient analysis method to estimate the effect on the variable of interest. When I was studying the method it gave me a hard time of statistical understanding. All committee advised me against the method. Dr. Palma helped me to look into the concept of the SCM and its properties. Dr. Bessler supported me in discovering the importance of the statistical significance and the robustness of the results. Dr. Stevens assisted me in selecting the control units to assess the effects well. Above of all, I want to thank Mr. Kazuya Tamura and Ms. Mari Nakamura who work for the Ministry of Internal Affairs and Communication in Japan. They allowed me to access the data related to climate change. I also want to thank Ms. Yinjunjie Zhang of the Dept. of Agricultural Economics in Texas A&M University. She gave me constructive advice whenever I encounter problems of the model method and the estimation process.

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INTRODUCTION

The Tōhoku earthquake with a magnitude of 9.0 in the Richter scale occurred on March 2011 in a nuclear site. It was estimated that 97,320 people went missing, and 164,865 Fukushima residents fled their homes. In addition, 760,000 metric tons of water stored at the nuclear plant was contaminated (Yamaguchi 2016). The natural disaster cost Japanese taxpayers over $100 billion and the country was forced to import more fossil fuels to meet energy needs (Cadman 2016). The Japanese government shut down nuclear reactors subsequently for safety inspections and only three reactors are currently operating (Slater-Thompson 2016). However, the government stated that nuclear power is still an important energy source, but only with strict safety protocols (Electricity Review Japan 2016).

Figure 1 shows the total amount of annual Greenhouse Gas (GHG) emission with the reduction targets set up by the government of Japan. Japan set a reduction target of 6% for the first commitment period from 2008 to 2012 after the adaptation of the 'Kyoto Protocol' in 1997. The actual GHG emissions during the first commitment period was above the target emission to the 1990 level and it increased 1.6% annually. However, the objective of GHG reduction was achieved in terms of deductions from forest carbon sequestration and carbon credit according to the global environment report of the Ministry of the Environment of Japan.

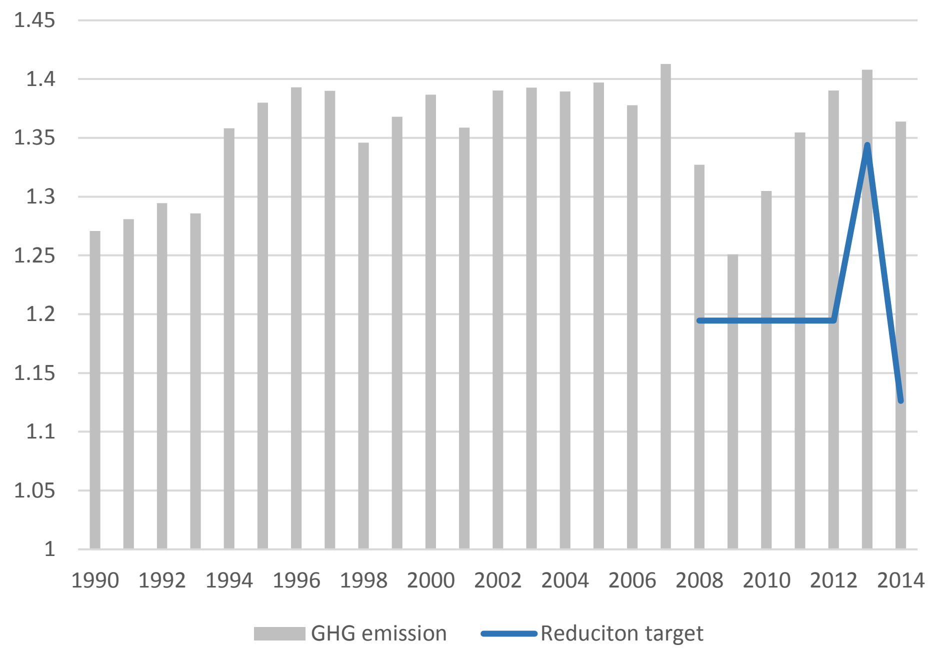

Figure 1: Japan GHG Emission (billion tons CO_2e) and GHG Reduction Target

In March 2012 the Japanese government notified the United Nations Framework Convention on Climate Change (UNFCCC) of the new mitigation targets for 2020. After the nuclear disaster, Japan issued the innovative strategy on energy and environment and it showed that it will decrease the nuclear power dependence by 2030. The target reduction of GHG emission[1] for 2030 is about 20% of the level in 1990. In December 2012 at the COP-18 in Doha, the government did not submit the reduction target.

[1] GHG (greenhouse gas) emission per capita is equivalent to tonnes of CO2 emission per capita. The 'Kyoto basket' of greenhouse gases include: carbon dioxide (CO2), methane (CH4), nitro oxide (N2O), and the so-called F-gases (hydrofluorocarbons, perfluorocarbons, nitrogen trifluoride (NF3) and Sulphur hexafluoride (SF6)). CO2, as we know, comes from natural and human that natural sources are decomposition, volcanoes, respiration, and so on. Otherwise, human sources include electricity generation, deforestation, and such like that. (Eurostat, http://ec.europa.eu/eurostat/web/products-datasets/-/t2020_rd300)

At the COP-19 in Warsaw, the new Japanese political party elected proclaimed the 2020 reduction of emission to be only 3.8% of the 2005 level. This Warsaw Target is far behind from the Copenhagen Pledge and it represents a 3.1% increase from the level of 1990 (Kuramichi 2014). One more change for the GHG reduction target was determined at the COP-21 in Paris and the target is a 26% reduction to the level of 2013 by 2030. Table 1 shows the timeline of how the Japanese GHG reduction targets changed over time. The reduction targets are still likely going to be changed dependency on the political circumstances of Japan.

Japan imports 94% of primary energy sources from various countries (Hayashi and Hughes 2013). Figure 2 shows imports of primary energy sources of Japan including coal, oil, natural gas, and side products of coal and oil. The straight line presents the amount of imports and the bar shows the percentage change between the previous and current year. Imports of primary energy sources increased by 2.84% after the nuclear disaster.[2]

[2] In 2008 and 2009 the import of primary energy sources shows negative percentages because of the global financial crisis.

Table 1: Timeline of Conference of the Parties and Japan's GHG Reduction Objectives

Timeline	What happened	Note
Dec 1997	Kyoto Protocol adopted at COP-3	• 6% reduction to the level of 1990 for the first commitment period (2008-2012)[3] • 25% reduction to the level of 1990 by 2020
Dec 2009	COP-15 in Copenhagen, Denmark	• 25% reduction to the level of 1990 by 2020
Dec 2011	COP-17 in Durban, South Africa	• Fukushima nuclear disaster occurred • 25% reduction to 1990 by 2020
Sep 2012	The Innovative Strategy from Japan	• 20% reduction to 1990 by 2030 (5-9% reduction to 1990 by 2020) • Phase out nuclear power by 2030
Dec 2012	COP-18 in Doha, Qatar	• The government can't have consensus on revised GHG reduction targets.
Nov 2013	COP-19 in Warsaw, Poland	• 3.8% reduction to 2005 by 2020[4] • 3.1% increase from the level of 1990
Dec 2014	COP-20 in Lima, Peru	• 20% reduction to 2013 by 2030
Dec 2015	COP-21 in Paris	• 26% reduction to 2013 by 2030[5]

Source: INDC (Intended Nationally Determined Contributions and National Institute for Environmental Studies, Japan)[6]

[3] Russia, Japan and New Zealand did not take second commitment period target. All Annex I countries, including those without targets under the second commitment period of the Kyoto Protocol, have 2020 targets under the UNFCCC. For details see http://climatechangeauthority.gov.au/appendix-b-global-action-reduce-greenhouse-gas-emissions

[4] The rate of GHG emission reduction included forest sequestration and overseas credits and assuming zero nuclear power.

[5] After the nuclear disaster, the administration of Shinzo Abe tried to set the GHG reduction target with revising the energy plan and mix. In consideration of the economic sustainability of the Japan the reduction target is established higher than the old one.

[6] The data in the table is collected and summarized from INDC, Kameyama (2015), Tsukimori (2015), and Masui and Kainuma (2010).

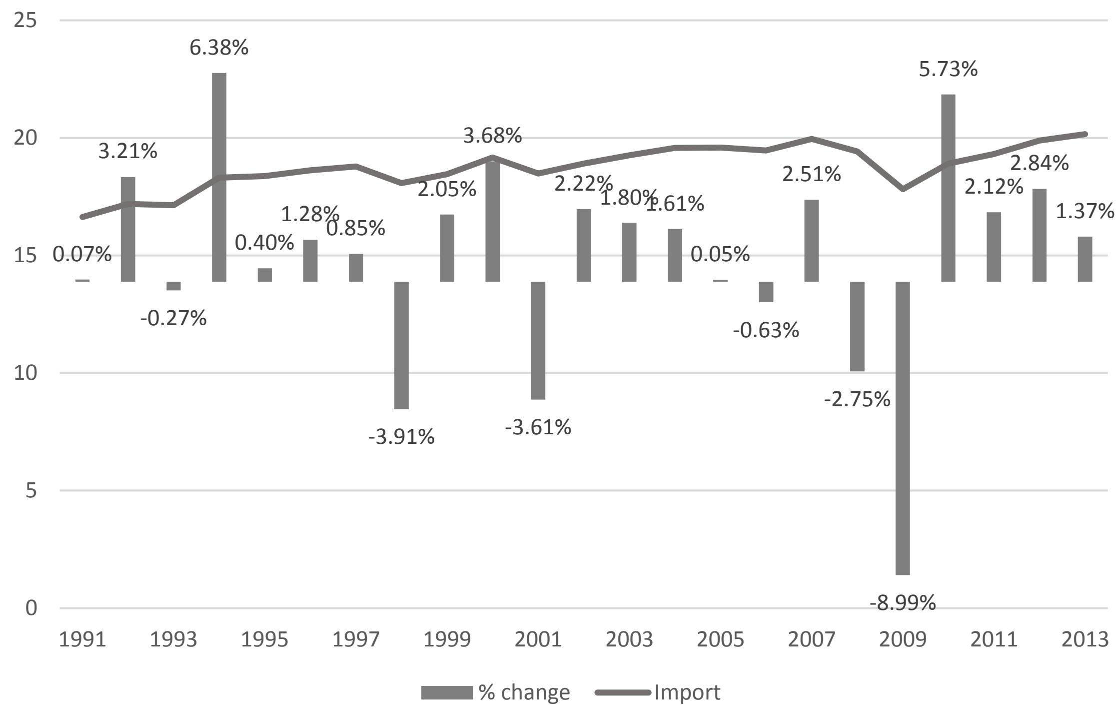

Figure 2: Japan Imports of Primary Energy Sources (thousand petajoules)

Figure 3 shows electricity generation in Japan by source. The sources are divided into six sectors: Hydro, thermal, nuclear, wind, photovoltaic, geothermal power, and other sources. In 2005 fossil fueled power shows 65.8% of the total electricity generation and the proportion is similar to the level of 2010. The distribution of fossil fuel increased by 90.2% whereas nuclear power decreased by 1.5% of the total generation after the natural disaster. In 2013, the proportion of nuclear power generation dropped slightly by 0.85%. It appears that the fossil fired power plant was replaced with the nuclear power plant for electricity generation. Due to the transition of power generation from nuclear reactor to fossil fueled plant, the industrial sector in Japan provided more greenhouse gases.

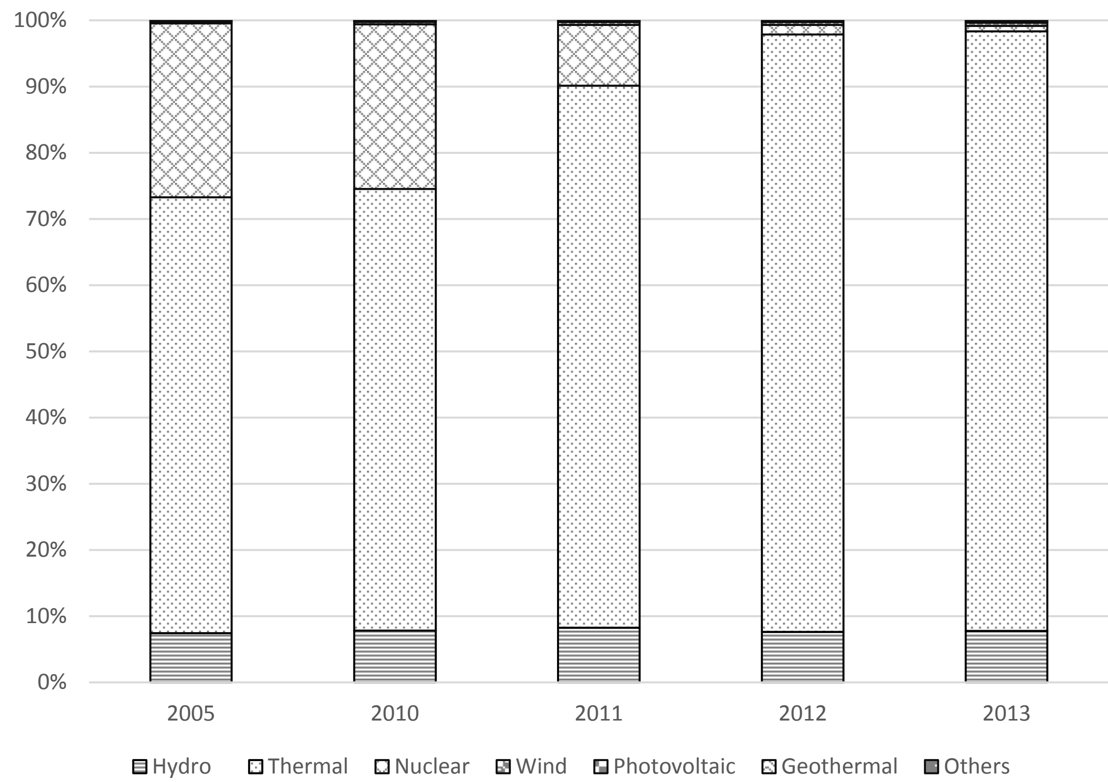

Figure 3: Japan Electricity Generation by Sources (percentage)

The change of the GHG emission is explained in the following steps. First, the shutdown of reactors by the Japanese government. This caused that Japan lost the ability to continue electricity generation. In addition, Japan needed to import more primary energy sources. That motivated thermal power generation increases up to over 90% of the total electricity generation.

Causal inference is used to evaluate the effect of the treatment on the outcome of interest. In this paper, the GHG emission[7] is the dependent variable of interest and the

[7] The variable of interest is the GHG emission per capita and the greenhouse gases is divided into four sub-components. The carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and fluorocarbons (F-

nuclear disaster is the treatment. The next step is to choose the method to be applied to the analysis. Table 2 shows the strength and weakness of each causal inference analysis tool.

Difference-in-differences (DID) is used to estimate the effect of the treatment over 200 data samples by using standardized mean difference, response ratio, and regression coefficients or odds ratio and risk ratio by the type of dependent variable (DeLia and Hoover 2012). The dimension of the dependent variable has to be a single dimension and a *t*-test is used to evaluate statistical significance. DID is applied to find the effect using variation over time in the treated unit identifying the significance of unobserved factors.

DID supports the assumption of a parallel trend and it can be often violated when researchers apply fixed effect models to estimate the causal effect. Xu (2016) proposed the generalized synthetic control method (GSCM) to mediate the problem. The matching design is used to find control units similar to the treated unit with an observing the same unobserved influence in both units (Sills et. al. 2015). Matching method is used to find the effect of the intervention with at least 200 samples. It can be applied to a single dimension of the dependent variable and *t*-test is needed for the statistical significance hypothesis.

In addition, Event study is adopted to assess the effect of the event of the firm publicly traded in the stock market. Simple relationship between the target firm's return

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gases) are include in the GHG emission. In this paper the emission from industrial used is the primary concern to the dependent variable.

and the industry or market including the treated unit. For the statistical significance, a *t*-test is used on the abnormal and cumulative abnormal returns.

Table 2: Strength and Weakness of the Each Causal Inference

Type of Causal Inference	Advantages	Disadvantages
Synthetic control method	• Identify potential endogeneity of treatment • Time-variant estimates of treatment effect	• Outlier units of outcome variable • Not easy to get a good treatment
Difference-in-differences	• Simple statistical test • Control observable / unobservable factors	• Large number of samples • Often violated of parallel assumption
Matching method	• No required of time-dimension • Extraction of endogenous variable	• Large number of samples • Inability to control of unobservable factors
Event study	• Estimate the effect for other market / industry • Single event application	• Samples publicly traded firms only • Single type of dependent

Source: Fremeth et. al. (2016)

In this paper, impact evaluation is used to measure the relationship between the treated unit's and control group's estimates in the absence of an earthquake. The synthetic control method (SCM) introduced by Abadie and Gardeazabal (2003) is used to study the impact of natural disaster, conflict, and political change. SCM shows an efficient and clear approach for selecting control units by similarity and provides statistical inference by placebo studies. It allows researchers to conduct analysis with relatively small samples in comparison to the other methods. The weighted average of the control unit from SCM is needed to make it feasible and close to the treated unit in similarity. The outcome of the control unit with optimal weight is pursuing the path of the treated unit in the pre-intervention period and it shows the distance path in the post-intervention period. The difference between the treated unit and the synthetic unit is called the effect of the intervention. This paper applies SCM to estimate the effect of a natural disaster on greenhouse gas (GHG) emission.

The paper applies the SCM to evidence the impact of the earthquake in Japan on GHG mission. The null hypothesis is there is no relationship between the intervention and GHG emission. The alternative hypothesis is there is a relationship between the intervention and the change of GHG emission. Section II shows a literature review of the analysis methods and, the application to study the effects of natural disasters. Section III is about the synthetic control method in comparative case studies. Section IV presents the results with visual graphs and tables. Lastly, section V concludes and discusses the implications of the results. The impact of the nuclear accident on the Japan. Finally, the limitations of the paper are presented in the last section.

LITERATURE REVIEW

The Synthetic Control Method (SCM)

Abadie and Gardeazabal (2003) introduced the SCM to analyze the effects of terrorism in the Basque's economy in Spain. They introduced SCM and showed the plausible results graphically; however the result can be contaminated by the economic downturn. Spain was facing at that time. Therefore, a simple comparison of the evolution of the Basque economy with the economy of the rest of Spain would not only reflect the effect of terrorism but also the effect of pre-terrorism differences in economic growth determinants. This motivated the additional tools to improve statistical inferences such as placebo studies, leave-one-out, the ratio of post to pre-intervention MSPE[8], and cross-validation in Abadie et al. (2015).

Robbins, Saunders, and Kilmer (2015) argued that SCM has a deficiency of dealing with micro-level data. The high dimensional and micro-level data with synthetic control method is to enhance synthetic comparison and joint statistical assessment. SCM can be used with multiple treated units and they introduced the 'omnibus test' that identify a treatment effect jointly across multiple outcomes. The method improves the precision of the estimates of the treatment, however the omitted variable biases result from failure in integration with a robust set of outcomes.

Kaul et al. (2016) argued that the synthetic control unit does not provide similarity to the treated unit's variable of interest in absence of the intervention. They

[8] Mean Squared Predictor Error

implied that the value of outcome variables in the pre-treatment period must be close to the treated unit's to attain similarity and it is defined as an outer optimization. On the other hand, Abadie et al. (2010) and Abadie et al. (2015) highlight the closeness between the synthetic control unit and the actual unit and defined the problem as an inner optimization.

Xu (2016) argued that generalized synthetic control method (GSCM) relaxes the violation of the parallel assumption in difference-in-differences (DID) and combines the SCM with linear fixed effects models. GSCM applies SCM with multiple treated units and changeable treatment time periods. Xu (2016) applied GSCM to analyze the effect of Election Day registration (EDR) laws on voter attendance in the United States. They found that EDR law has a positive impact on voter turnout.

Empirical Applications of the SCM Analysis

Ando (2015) shows that the establishment of a nuclear power facility affects the local economies in terms of income and employment. She tested SCM with eight municipalities as the treated unit and set up the synthetic control units of coastal municipalities within the same region as the treated areas. The results showed that employment and income are statistically significant. The diversity presented in multiple treated units is explained by examining each unit's effect on the local economies.

Gong and Rao (2016) analyzed the effects of political instability in Fiji on economic growth using SCM. It is different to empirically analyze the effects of political unrest and economic growth. They constructed a synthetic Fiji by choosing 13 commonwealth countries with similar population size. They showed statistically significant negative impacts in GDP per capita between synthetic Fiji and actual Fiji using placebo and robustness tests.

Kreif et. al (2015) shows a comparison with the DID estimation and the SCM in evaluating the effect of the health policies of P4P (pay-for-performance) initiative[9]. The difference between the two methods is the DID has constant effects of unobserved factors whereas the SCM has changeable effects of unobserved factors over time. The paper selects 24 hospitals in the North West region as the treated unit and the 132 hospitals in the rest of England as the control unit. The 24 treated units are aggregated into a single unit and the 132 control units to nine control regions. They analyzed the average treatment effect of the treated (ATT) estimates. The outcome of interest is 30-day risk adjusted hospital mortality and the results show there is no treatment effect prior to the treatment. The negative impacts is shown after the introduction of the AQ (advancing quality) scheme.

Dupont IV et al. (2015) evaluated the impact of the Great Hanshin-Awaji earthquake of 1995 on the Kobe economy. They collected a big size panel data consisting of over 1,000 municipalities over 30 years in Japan. The data was used to obtain a synthetic control unit and avoid idiosyncratic shocks affecting the results. The implication of the paper is to consider the proximity of control units to the treated unit.

[9] P4P is the payment model for the physicians, hospitals and healthcare providers evaluating the process of quality and efficiency.

The municipalities near the area affected by the natural disaster showed negative effects in the short-run whereas the areas outside seemed to be isolated from this effect.

Coffman and Noy (2011) applied SCM to estimate the impact on the economy by the hurricane Iniki on the Hawaiian island of Kauai. The dependent variables used in their analysis included private sector employment, resident population, personal income, and real per capita income. The results showed a negative effect on private sector employment, resident population and personal income. However, real per capita income had a positive effect, since the population was reduced in the early post-intervention period.

Billmeier and Nannicini (2011) looked at the effect of economic liberalization on per capita GDP. The liberalization is assessed if the country had socialistic economic structure such as controlled exports. Their dataset covers 180 countries during the period 1963-2000. The extent of measuring economic liberalization is based on a binary indicator by Sachs and Warner (1995). The results using SCM shows a positive impact on the trajectory of the variable of interest.

Gobillon and Magnac (2013) shows that the spatial dependence among the local sample units is critical to the evaluation of the regional policies. The outcomes is possibly correlated in the panel data. They present a comparison of the SCM and DID using Monte Carlo experiments. The paper emphasizes that the selection of control units neighboring the treated unit leads to biased estimates because the control units may be affected by contamination effects. On the other hand, it shows the factor loadings can remove the spatial correlation.

METHODOLOGY

Identification and Data

The synthetic control method (SCM) needs to meet two main requirements. The treated unit is affected by the intervention. In addition, the set of untreated units (donor pool) are required to have structural similarity to the treated unit, but it should be unaffected by the intervention. The donor pool is analogous in terms of covariates in regression or matching (Sills et. al. 2015). It is important to limit the pool with characteristics related to the treated units.

The treated unit is Japan and the type of intervention is a natural disaster. The Great East Japan Earthquake, Tōhoku earthquake, occurred in March 2011 is the analysis' treatment. The outcome variable is the GHG emission per capita and the intervention window is the period of 1995-2014 (pre-intervention: 1995-2010 and post-intervention: 2011-2014). The donor pool includes the 37 countries from the Organization for Economic Co-operation and Development (OECD), the United Nations Framework Convention on Climate Change (UNFCCC). The sources of GHG emission are broadly divided into six major parts such as electricity production, transportation, industry, commercial & residential, agriculture, and land use and forestry.[10]

[10] For details see https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions

Table 3: Variables of Synthetic Control Method

Variables	Description
Dependent variable	Greenhouse gas emission (1995-2014)
Treated country	Japan
Donor pool (the set of control units)	37 countries
Predictors (average over the pre-intervention period)	· Detailed sectoral ratios of employment (agriculture, mining & quarrying, construction, manufacture, utility, services) · Non-medical determinants (total fat, total calories, total protein, sugar, vegetable, and fruit) · Population ratio over the total population (15 & 64 years and over 65 years old) · GDP per capita (based on PPP, current USD) · GDP growth rate
Intervention year	Year when Fukushima nuclear disaster occurred (Year of 2011)

Source: OECD, UNFCCC, WRI, CDIAC, and department of labour in each country

The predictors applied in the model are shown in Table 3 and the data are from the Climate Analysis Indicator Tool (CAIT) of the World Resources Institute (WRI), the Carbon Dioxide Information Analysis Center (CDIAC), and the statistical agencies of each country. The employment ratio by sectoral economic activity are from the OECD and the department of labor of each country. Non-medical determinants including total fat, protein, calories, sugar, fruit, and vegetable is from the OECD and the Food and Agriculture Organization of the United Nations (FAO). The intake of nutrition affects

GHG emission since human-sourced emissions have increased due to diet. Changes through meat consumption footprint is about two times higher than vegetarian's and carbon intensity can be identified by diets. (fruit: 4.6, vegetable: 2.8, sugar: 0.6, beef: 14.1, oil: 0.8, and drink: 2.2 $gCO_2e/kcal$)[11]

Synthetic Control Method

The objective of SCM is to estimate the effect of the intervention on the outcome for the treated unit in the post-intervention period. Assume that there are observable units $i = 1, 2, \ldots, J$ and time periods of $t = 1, 2, \ldots, T_0, T_0+1, \ldots, T$. Without loss of generality, the treated unit is $i = 1$ and the donor pool is $i = 2, \ldots, J$. The pre-intervention period is $t = 1, \ldots, T_0$ and the post-intervention period is $t = T_0+1, \ldots, T$ (Abadie et. al. 2010).

Constructing the donor pool is a critical step for getting an acceptable estimate and two outcomes derive from SCM. The outcome, Y_{it}^{N}, is not exposed to the intervention at time t and unit i. The outcome, Y_{it}^{I}, is exposed to the intervention at time t and unit i. The effect of the intervention is defined by the difference between Y_{it}^{I} and Y_{it}^{N} that $\alpha_{it} = Y_{it}^{I} - Y_{it}^{N}$ in the post-intervention period. The process of finding any potential effect, α_{it}, is displayed graphically by Silles et al. (2015) in Figure 4.

$$Y_{1t} = Y_{it}^{N} + \alpha_{it} \cdot D_{it} \tag{1}$$

$$\alpha_{it} = Y_{1t} - Y_{it}^{N} v \tag{2}$$

[11] For details see http://shrinkthatfootprint.com/food-carbon-footprint-diet

To find any potential effect, α_{it}, in the post-intervention period, the two outcomes are needed in the equation (1). The actual outcome of the treated unit is known and the outcome of the synthetic control unit is from the weights. There are four vectors needed to get the weights: X_1 is a vector of predictor's values of the treated unit (k × 1), X_0 is a vector of predictor's values of the control units (k × J), Z_1 is a vector of outcome's values of the treated unit (T_0 × 1), and Z_0 is a vector of outcome's values of the control units (T_0 × J) (Sills et. al. 2015).

$$\widehat{\alpha_{it}} = Y_{1t} - \sum_{j=2}^{J+1} W_j^* \cdot Y_{jt} \qquad (3)$$

The effect of the treatment in the equation (3) can be derived from the actual outcome of the treated minus the outcome of the synthetic control unit with the optimal weights on the each control unit. To constructing the synthetic control unit, the two weights, *W* and *V*, are needed from the donor pool. *W* is the weights on each control unit and minimizes the distance of the predictors in the pre-intervention period in equation (4). It makes the closest synthetic control unit and this optimization is called inner optimization by Abadie et. al. (2003). A vector of weights $W = \left(w_2, \ldots, w_J\right)'$ such that $w_i \geq 0$ for $i = 2, \ldots, J$ is defined to develop a synthetic control unit and $w_2 + \cdots + w_J = 1$. We can use the optimal weight $W^* = (W_2^*, \ldots, W_{J+1}^*)'$ to get the effect of the treatment (Jaquette et. al. 2016).

Another weight, *V*, is used to find optimal predictor values and it minimizes the distance of the outcomes of the treated and control units in the pre-intervention period in the equation (5). It makes minimized mean squared prediction error (MSPE) of the outcome of the treated and control units. This is called outer optimization and Abadie et.

al. (2010) shows that the use of two optimization gives asymptotically unbiased estimates of the treated unit.

$$W^* = \underset{W}{argmin} \sqrt{(X_1 - X_0W)'V(X_1 - X_0W)} \tag{4}$$

$$V^* = \underset{V}{argmin} \big(Z_1 - Z_0W^*(V)\big)'\big(Z_1 - Z_0W^*(V)\big) \tag{5}$$

$$\sum_{m=1}^{k} v_m(X_{1m} - X_{0m} \cdot W)^2 \tag{6}$$

v_m in equation (6) is a weight that reflects the importance of variable *m* as a predictor of the dependent variable. *V* is a non-negative diagonal matrix with each predictor's values (v_m). By choosing *W* and *V*, the pre-treatment outcome of the donor pool is close to the pre-treatment outcome of the treated unit. Abadie and Gardeazabal (2003) stated *V* with minimized mean squared prediction error (MSPE) and *W* with optimal *W** give a good fit to the model. The outcome of the control unit is from the factor model in the equation (7). Let δ_t is an unobserved common time-dependent factor across units, Z_i is s vector of observed covariates to predict the outcome (r × 1), θ_t is a vector of unknown parameters (1 × r), μ_i is a vector of unknown factor loadings (r × F), λ_t is a vector of unobserved common factors (1 × F), and ε_{it} is unobserved idiosyncratic shocks.

$$Y_{it}^N = \delta_t + \theta_t Z_i + \lambda_t \mu_i + \varepsilon_{it} \tag{7}$$

$$\sum_{i=2}^{J} w_i Y_{it}^N = \delta_t + \theta_t \sum_{i=2}^{J} w_i Z_i + \lambda_t \sum_{i=2}^{J} w_i \mu_i + \sum_{i=2}^{J} w_i \varepsilon_{it} \tag{8}$$

The weight, *W*, is indexed to the outcome of control unit and the optimal weight, *W**, applied to find the synthetic control unit. With the optimal weight the outcome of synthetic control unit and predictor's characteristics are derived in the pre-intervention in equation (9).

$$\sum_{i=2}^{J} w_i^* \, Y_{i1}^N = Y_{11, \ldots,} \sum_{i=2}^{J} w_i^* \, Y_{i1}^N = Y_{1T0} \; and \; \sum_{i=2}^{J} w_i^* \, Z_i = Z_1 \qquad (9)$$

Assumptions of the Synthetic Control Method

To construct the synthetic control unit minimized the distance to the treated unit the selection of the donor pool is a decisive step. Five assumptions need to be considered (Fremeth and Holburn 2016). First, the donor pool should contain a large number of units unaffected by the intervention. In this paper, 28 countries were first included in the donor pool, however, the list was reduced to six units following placebo studies. That means there is no statistical significance because the p-value is 1/6 (0.166).[12] Second, the untreated unit should not experience the treatment in the post-intervention period. The idiosyncratic shock is assumed as the political changes affected by the nuclear disaster.[13]

[12] P-value is the probability in terms of rejecting the null hypothesis when it is true. My previous analysis of using 28 control units shows 1/6 (0.166) and it said that 166 in a thousand chance of being wrong. That is statistically 83.6% significant.

[13] After the Fukushima nuclear disaster the large protests occurred in Germany, but the country did not shut down the reactors. The prime minister announced that all reactors will be closed by 2022. Costa Rica and Cyprus were included in the donor pool because the two countries never have nuclear power plant in their countries. It can be said that the two units are not experienced the profound shock after the nuclear disaster and there is no reason to be excluded from the donor pool by Abadie et. al. (2015).

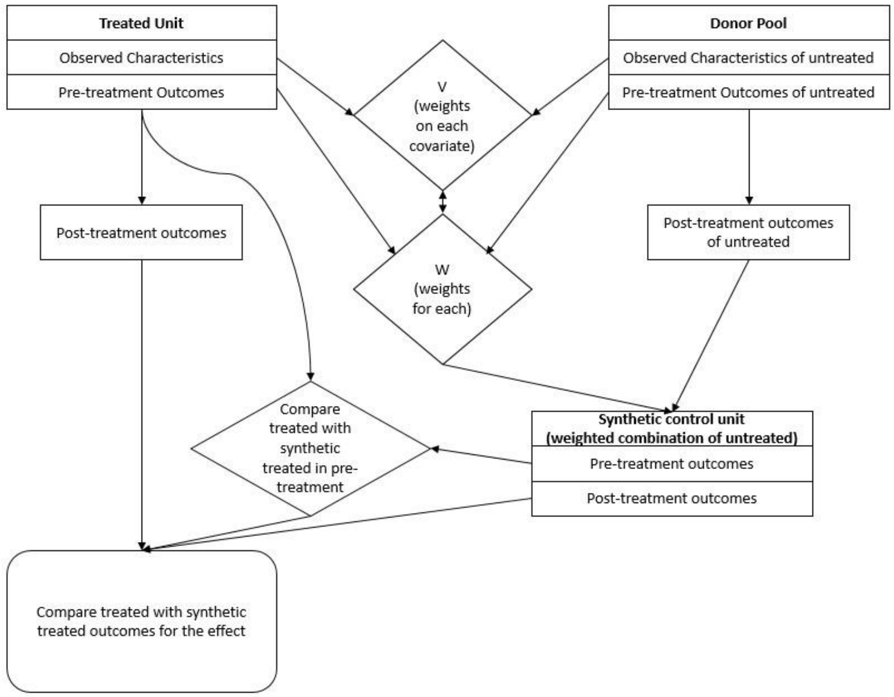

Figure 4: Graphical Scheme of Synthetic Control Method[14]

Third, the countries in donor pool are not affected by the intervention. South Korea and China are eliminated from the list since there is a profound shock by the radiation spread even if two countries are not directly affected by the intervention. Fourth, the countries with missing observations are to be excluded (Jaquette et. al. 2016). Lastly, it is important to restrict the donor pool to units with similar characteristics to the treated unit. The papers using SCM selects the control units by the feature of predictors affecting the dependent variable. The outcome variable, GHG emission, is mostly influenced by the structure of industry and gross domestic production (GDP).

[14] Reprinted with the open access article distributed under the terms of the Creative Common Attribution License of Sills et. al. (2015). For details see https://creativecommons.org/licenses/by/4.0/

I give priority over the employment ratio to set up for the donor pool. The countries with similar industrial formation can give an approximate synthetic control unit. However, if the characteristics of control units are artificially matched, there is a chance of overfitting problem. The good fit of the model can result from the method but there was no statistical significance in the placebo studies. Abadie et. al. (2015) shows that the application of cross-validation to the model for non-natural matching (Abadie et. al. 2015).

RESULTS

The results presented in this section include the predictors' estimates used in the model and weights of each country in the donor pool.[15] The graphical result of GHG emission per capita in Japan and synthetic Japan is provided by the synthetic control method. The gaps between the two units are added for comparing the emission in pre- and post-intervention period. The subsection placebo studies provide graphs to validate statistical significance of the results. Four placebo tests are performed by excluding units having relatively large mean squared prediction error (MSPE) to the treated unit. In addition, the "leave-one-out" test is conducted to evaluate the robustness of the model. The ratio of post-intervention to pre-intervention MSPE is presented for checking the statistical significance of the results. Table 4 shows the estimates of Japan and synthetic Japan by predictors.[16]

The values of predictors are close to each other but total fat, fruit, and sugar supply show big differences between Japan and synthetic Japan. These predictors can be excluded from the model. The reason why the indicators are included in the model is the nutrition index affecting the GHG emission. One of the requirements in the previous section for the construction of the donor pool is the selection of predictors. The human-sourced predictors, the nutrition index, are assumed not to be related to industrial

[15] All the results from the analysis use the R-Package for statistical calculation. The syntax is used in the statistical software is collected and modified to apply the data and method of the paper. I refer to Becker et. al. (2016) and Hainmueller et. al. (2015).

[16] The data of employment ratio and population used in Table 4 is from multinational statistical agencies. (Ministry of Finance of Cyprus, National Institute of Statistics and Census of Costa Rica, National Institute of Statistical and Economic Studies of France, and National Institute of Statistics of Romania)

emission. However, it is the indicators showing the similarity between the treated unit and the control units. The employment ratio of the country is the essential predictor for building up the donor pool.

Table 4: Pre-Intervention Characteristics

		Japan	Synthetic Japan
GHG emission per capita [a]		9.816	9.799
Employment ratio by sectoral industry [b]	Agriculture & Fishery	4.463	6.714
	Mining	0.063	0.983
	Manufacture	18.364	17.942
	Utilities [c]	0.527	1.111
	Construction	9.146	8.206
	Services [d]	66.384	65.043
Non-medical determinants [e]	Total fat supply	88.745	116.701
	Total calories supply	2804.273	3082.256
	Total protein supply	92.291	90.912
	Sugar supply	28.745	43.460
	Vegetables supply	106.027	96.939
	Fruits supply	54.855	70.986
Population ratio [f]	15-64 years old population	66.743	67.608
	Over 65 years old population	19.102	12.807
GDP per capita		28.325	21.691
GDP growth rate [g]		0.382	3.270

Source: Computation from the data

[a] GHG emission per capita (thousand kilograms), average for 1995-2010
[b] Percentage of employed person in the industries over total employed population, 2002-2007
[c] Utility industries divide into electricity, gas, and water
[d] Services divide into real estate, life-related, entertainment, food & beverage, and technical service
[e] Each item has its own unit by yearly or daily consumption, average for 2000-2010
[f] Percentage over total population, 1995-2010
[g] Percentage change of GDP in annually, average for 1995-2010

Table 5: Weight for Each Control Unit

Country	Synthetic control	Regression weight	Country	Synthetic control	Regression weight
Australia	0.181	0.00	Slovak Republic	0.000	-0.04
Austria	0.000	-0.34	Slovenia	0.000	-0.02
Belgium	0.124	0.00	Sweden	0.000	0.40
Chile	0.252	0.17	Switzerland	0.000	-0.03
Czech Republic	0.205	0.07	Turkey	0.000	-0.01
France	0.000	-0.10	United Kingdom	0.000	0.30
Germany	0.000	0.51	United States	0.000	0.04
Greece	0.000	-0.22	Brazil	0.000	-0.16
Hungary	0.000	-0.15	Colombia	0.000	-0.27
Iceland	0.000	-0.21	Costa Rica	0.000	-0.29
Ireland	0.000	-0.21	Indonesia	0.000	0.28
Israel	0.000	-0.10	Russia	0.000	0.26
Italy	0.000	0.30	Lithuania	0.000	0.33
Mexico	0.000	0.22	Croatia	0.000	-0.11
Netherland	0.000	0.23	Bulgaria	0.153	0.19
New Zealand	0.000	0.24	Cyprus	0.085	0.33
Norway	0.000	-0.20	Romania	0.000	-0.13
Poland	0.000	-0.39	Latvia	0.000	-0.15
Portugal	0.000	0.26			

Source: Computation from the data by SCM

The weights of each control country in synthetic Japan are shown in Table 5. Each unit of Australia (18.1%), Belgium (12.4%), Chile (25.2%), Czech Republic (20.5%), Bulgaria (15.3%), and Cyprus (8.5%) contributes to the GHG emission per capita in Japan prior to the intervention with the number in the parentheses. That means the optimal synthetic control unit is created by the combination of weighted countries. Regression weights come from the linear combination of untreated control units. It is an alternative way to construct the synthetic control unit. However, the regression weight show negative values or greater than one in the Table 5.

Figure 5 shows the GHG emission per capita in Japan and synthetic Japan during the period of 1995-2014. Synthetic Japan's GHG emission per capita closely follows the trajectory of Japan's for the pre-intervention period. The emission per capita starts to diverge in 2011 when the natural disaster occurred. However, the two trajectory lines of Japan and synthetic Japan are not exactly on the same pathway in the pre-intervention period, since the *V* and *W* may not fully minimized. The effect on the GHG emission per capita between Japan and synthetic Japan increases after the intervention because all the reactors were halted for safety inspections. Then, the electricity generation was transferred from nuclear reactors to coal and natural gas based power plants.

Figure 6 displays the yearly gaps in the GHG emission per capita between Japan and synthetic Japan. The difference is between plus/minus one percent prior to the intervention but it shows the deviation after the natural disaster. There is a reduction in 2007-2008 from Japan and the donor pool that comes from the first commitment period (2008-2012) of the 'Kyoto Protocol' and the financial crisis (Ministry of the

Environment 2014). The countries under the initiative have responsibilities to decrease GHG emission followed by their industrial condition.

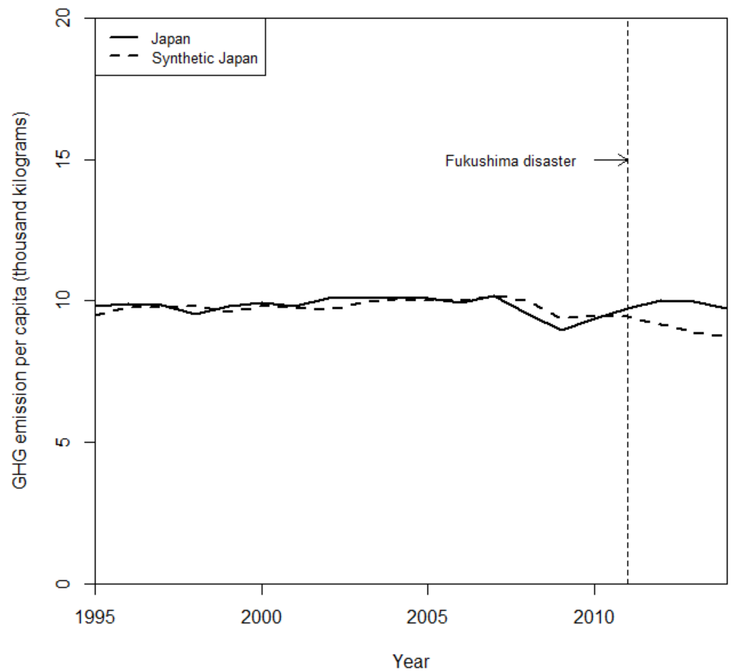

Figure 5: GHG Emission per capita of Japan and Synthetic Japan

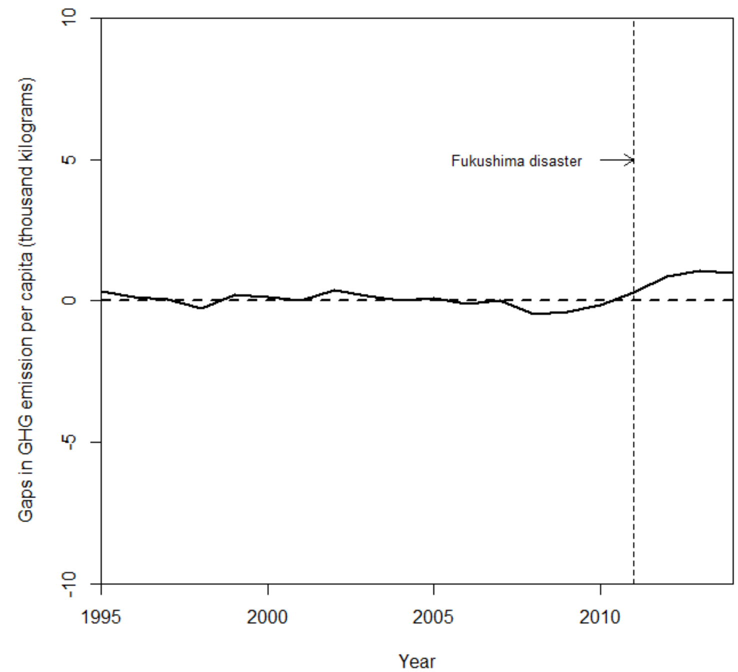

Figure 6: Gaps in GHG Emission per capita of Japan

Placebo Studies

Statistical inference is important to support the estimates of the synthetic control method. Abadie et al. (2003) presented a series of tests to be used to evaluate the significance of the results. The placebo tests are performed by iteratively applying the synthetic control method to each country in the donor pool. If the gaps from placebo tests show notable magnitude between tested country and synthetic tested country, the estimate does not provide significant evidence of the intervention (Abadie and Gardeazabal 2003).

Figure 7 shows the placebo tests with all 37 countries in the donor pool and the pre-intervention mean squared prediction error (MSPE) in Japan is 0.016 and median MSPE 0.034. This test shows a good fit for GHG emission per capita prior to the intervention. Another placebo test shows the worst fit having insignificantly distant MSPE. The United States shows MSPE of 5.73 since the country indicates the highest GHG emission per capita during 1995-2010. Therefore, synthetic Japan does not show a good fit for GHG emission per capita before the intervention and it affects the variable of interest in the post-intervention. Accordingly, the United States needs to be excluded, because it has much higher MSPE compared to the rest of the donor pool.

Figure 8 shows the results of the placebo test that excludes countries with MSPE 20 times higher than Japan. Australia and the United States are discarded and there are still substantial deviations from zero. The placebo test applies a lower cutoff in Figure 9 (five times) and Figure 10 (two times). Seven countries were excluded and nine countries were finally discarded in Figure 10. The last placebo test, Figure 10, with 19 unaffected units indicates unusual positive effects of the intervention in GHG emission per capita. The probability of a random permutation of the intervention is 1/19 = 0.052 and it has 95% statistical significance in the model.[17]

Figure 11 shows the leave-one-out test and it evaluates the sensitivity of the results. The optimal *W** from the process is to minimize the distance between Japan and synthetic Japan in the pre-intervention period (Abadie 2015). Abadie (2015) applied the test with the units having positive weights. In this paper, Australia, Belgium, Chile, Czech Republic, Bulgaria, and Cyprus are tested with synthetic Japan by leaving out each country one at a time. The gray lines of synthetic Japan reproduced leaving one of the six countries and they are close to each other. There are gaps between actual Japan and six gray lines. It implies that the model is robust to exclude any particular country (Gong et al. (2016)).

Figure 12 displays that the ratio of the post-intervention period MSPE to pre-intervention period MSPE for all 37 countries. The ratio of Japan stands out and the post-natural disaster MSPE is 123.724 times the pre-natural disaster MSPE. The second highest ratio is Cyprus of 48.916 that shows the ratio of Japan is 40% bigger than Cyprus'. The probability of obtaining such as big ratio like Japan is 1/37 = 0.027 (2.7%) when any country randomly experiences the intervention. Table 6 presented the ratio of

[17] The statistical inference of the SCM shows the statistical significance by how the synthetic control unit is close to the treated unit. That means how many control units remain after the placebo studies. Figure 10 shows 19 units after excluding countries having two times higher MSPE than Japan. The synthetic control unit is close to the treated unit as the probability of 1/19 (0.052) and shows 95% significance of proximity.

post-intervention to pre-intervention MSPE and RMSPE. Japan's ratio of both indicative ratios is clearly far from the rest of countries.

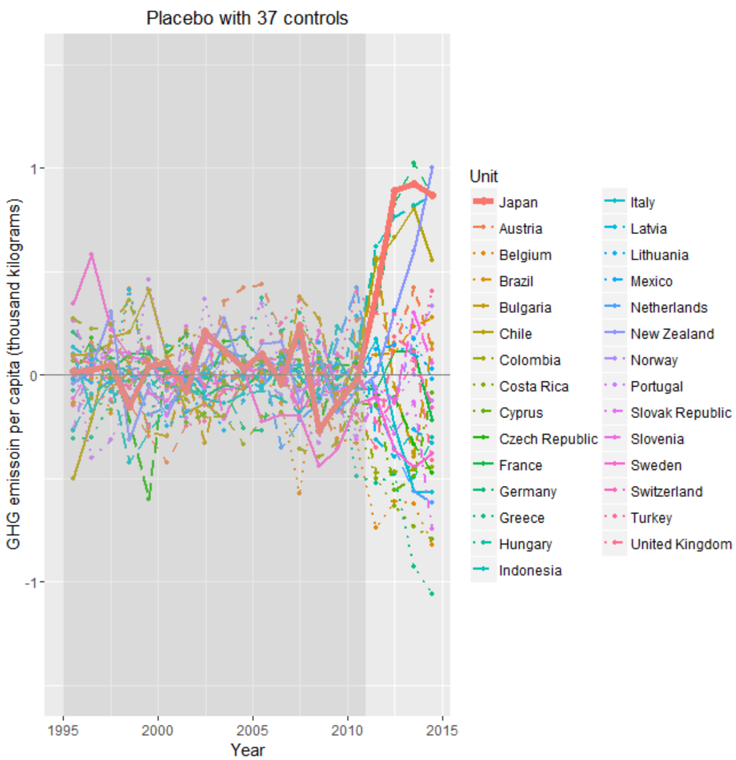

Figure 7: Placebo Studies with all the 37 Control Countries

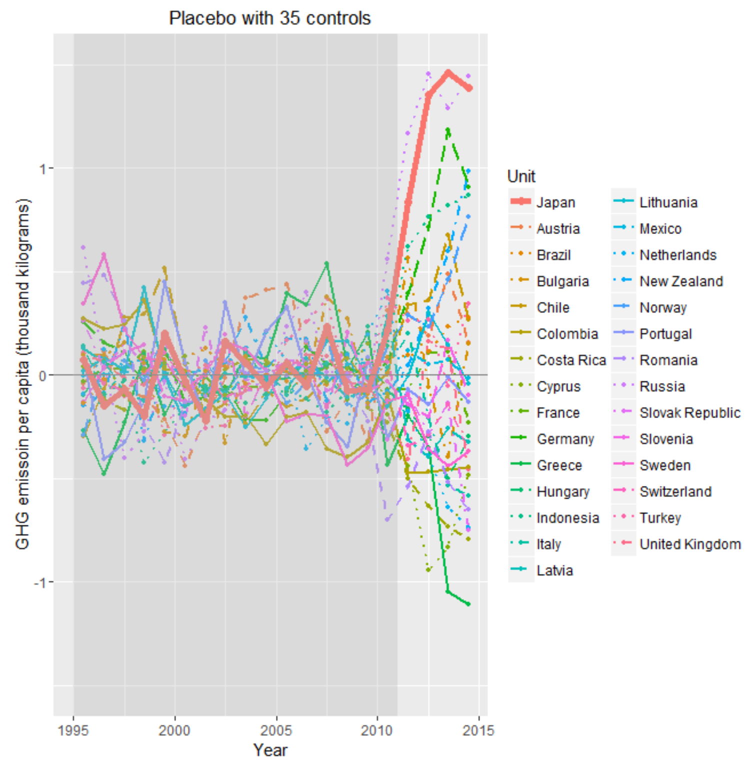

Figure 8: Placebo Studies with 35 Control Countries

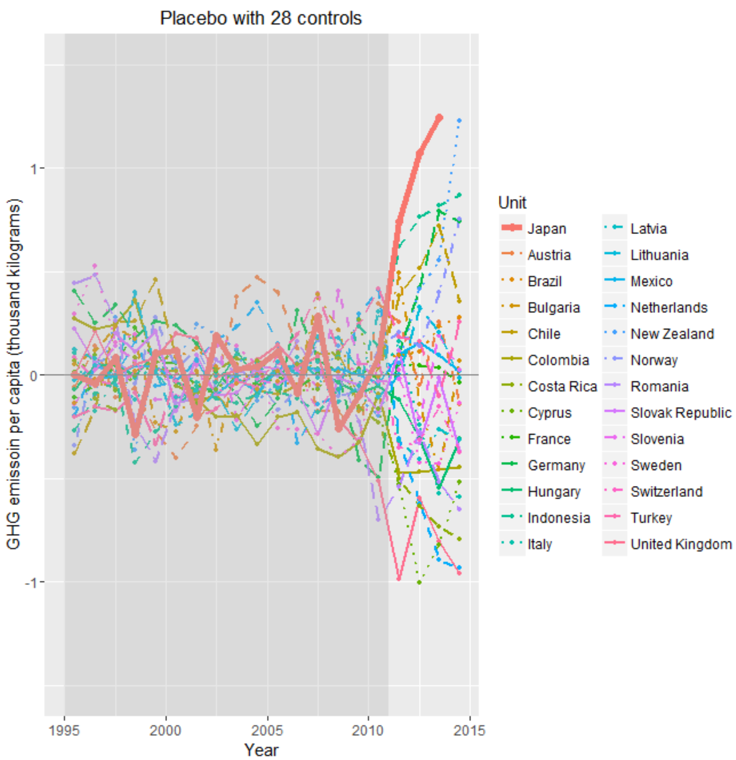

Figure 9: Placebo Studies with 28 Control Countries

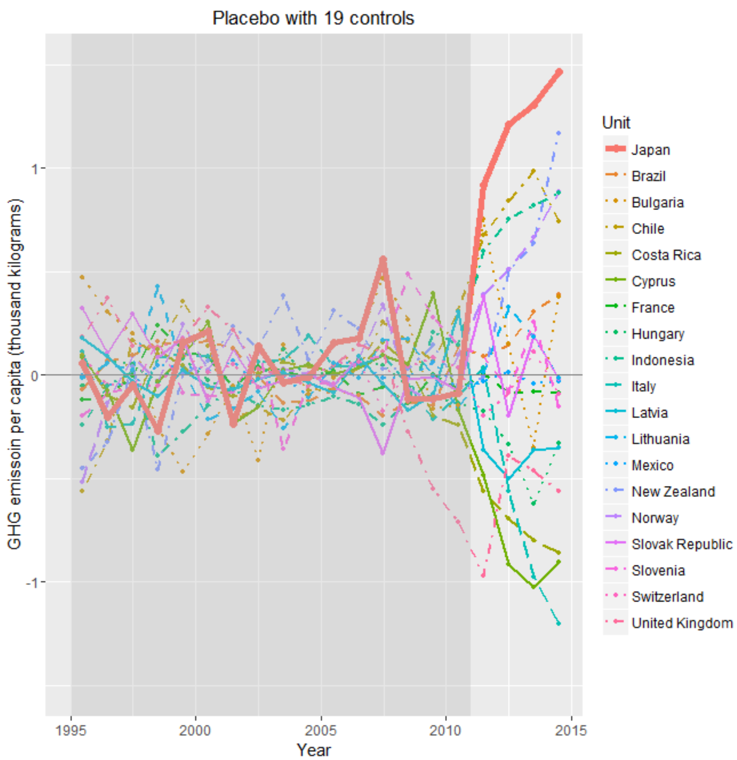

Figure 10: Placebo Studies with 19 Control Countries

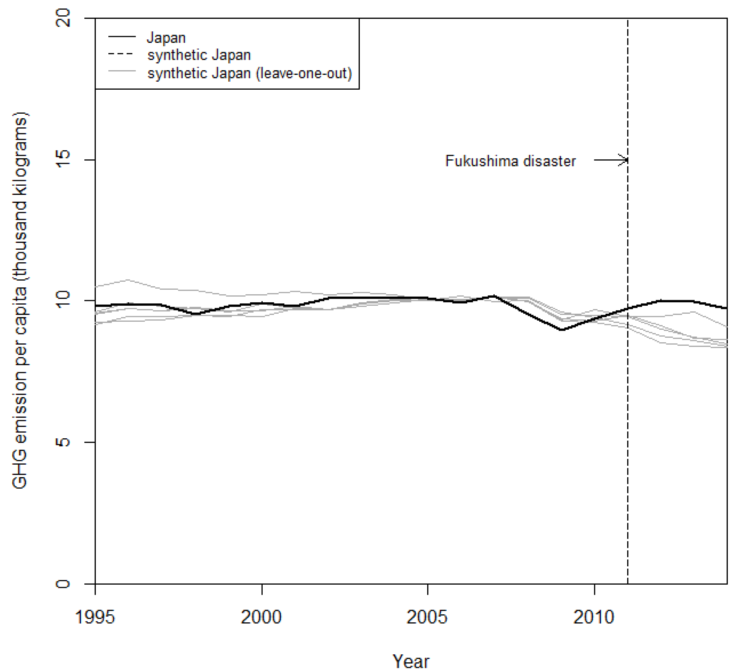

Figure 11: Leave-One-Out Distribution of the Synthetic Control of Japan

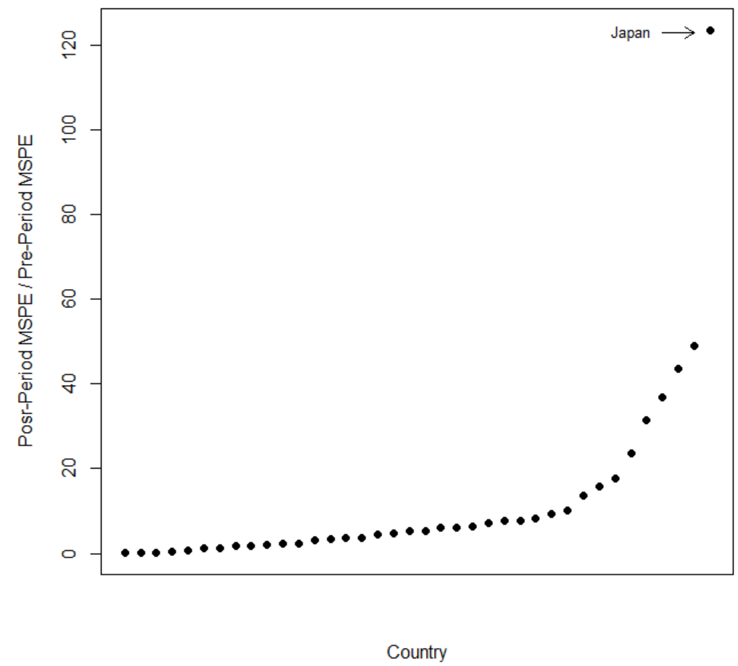

Figure 12: Post-Period MSPE / Pre-Period MSPE of Japan

Table 6: MSPE / RMSPE Ratio of Post-to-Pre-Intervention for Placebo Studies

Country	MSPE ratio (Post/Pre)	RMSPE ratio (Post/Pre)	Country	MSPE ratio (Post/Pre)	RMSPE ratio (Post/Pre)
Japan	123.724	11.123	Portugal	0.119	0.346
Australia	1.949	1.396	Slovak Republic	7.162	2.676
Austria	1.226	1.107	Slovenia	1.804	1.343
Belgium	8.307	2.882	Sweden	2.311	1.520
Chile	4.742	2.178	Switzerland	5.395	2.323
Czech Republic	2.259	1.503	Turkey	1.709	1.307
France	5.220	2.285	United Kingdom	9.383	3.063
Germany	43.530	6.598	United States	0.091	0.302
Greece	6.272	2.504	Brazil	7.704	2.776
Hungary	23.663	4.864	Colombia	3.451	1.858
Iceland	0.725	0.851	Costa Rica	36.796	6.066
Ireland	7.701	2.775	Indonesia	17.832	4.223
Israel	4.572	2.138	Russia	15.869	3.984
Italy	31.534	5.616	Lithuania	1.113	1.055
Mexico	13.685	3.699	Croatia	0.071	0.266
Netherland	6.184	2.487	Bulgaria	3.548	1.884
New Zealand	5.968	2.443	Cyprus	48.916	6.994
Norway	3.739	1.934	Romania	3.193	1.787
Poland	0.463	0.680	Latvia	10.069	3.173

Source: Calculated by the package of ‘MSCMT’ in R

CONCLUSION

The synthetic control method is used to evaluate the effect of interventions with a limited number of observations. It quantifies the impact of the intervention by building up the synthetic control unit (Fremeth and Holburn 2016). The tsunami from Tōhoku earthquake caused a wide meltdown of nuclear reactors located in the eastern Japan. As a result, electricity generation in Japan was seriously affected. The Japanese government requested to be excused for increasing the fossil fueled plants' operations.

The synthetic control analyzes the observational data of treated and control unit and estimates the impact on the GHG emission. The hypothesis established is set up and the null hypothesis is rejected by showing the graphical results with the placebo studies. There is an impact on the GHG emission by the natural disaster and it shows a rise in the post-intervention period. Placebo studies including a series of placebo test, leave-one-out test, and the MSPE ratio between post to pre-intervention is performed to assess the statistical inference of the results. All the tests show robust evidence of the statistical significance of the results.

Implications

There are implications for applying the SCM. First, researchers must consider the geographical proximity when an intervention related to the spatial dependence. The treated country, Japan, was not under a simple reactor malfunction but it was affected by a huge meltdown with radiation leaks. The nuclear spills went into the water and spread out through the Pacific Ocean. Almost every municipality in Japan was affected by side effects from the spread directly or indirectly. Spatial dependence of the control units neighboring the treated unit can cause the biased estimates (Gobillon and Magnac (2013)). For instance, Gong and Rao (2016) selects the control countries by similar population size for gross domestic production per capita. They assumes the analogous in the population size can affect the GDP per capita. Ando (2015) selects the control regions neighboring the target area. Her case is to estimate the local economic growth by the establishment of the nuclear power plant. That makes her to collect the control unit having similar regional attributes but only difference is the existence of the plant.

Second, the number of units in the donor pool is important to improve statistical significance. The SCM performs well with limited data but there can be problems with the sensitivity and the robustness of the results. In other word, the DID, event study, and matching method apply a *t*-test for statistical significance, the SCM measures how the closeness of synthetic control unit to the treated unit as a way to check the statistical inference. A couple of dozen samples is generally useful to get the goodness of fit model and robustness in the analysis but there is no possible number of units defined for the statistical significance.[18]

Third, the selection of predictors used in the analysis should be carefully considered for the reliable results. The predictor unrelated to the dependent variable makes unexpected shock with an insignificant conclusion. The researchers need to check the correlation between the variables prior to execution the synthetic control method.

[18] Gong and Rao (2015) uses only the 13 control units for the analysis.

Lastly, the problem occurs with the overfitting should be careful. The process of artificial selection of the control unit having similar outcomes can cause stable results. But it may show the insignificant results by the placebo studies. The synthetic control method is a good tool to find any potential effect of the specific intervention on the outcome of interest. It can be used to evaluate policies in case of future intervention using the prediction of how the outcome changes. There is further research for improving the SCM: (1) the way to meditate regional dependence problem, (2) more standardized method to find factors affecting the dependent variable.

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APPENDIX

The control unit of the paper is based on the countries belongs to the OECD and the UNFCCC. The treatment is related to the nuclear disaster affecting the treated and the control units directly or indirectly. By the spatial dependence, South Korea and China of the control unit are excluded. There is another requirement of selecting the control unit. The countries without nuclear energy can be alternative control unit. If the treatment is related to nuclear power generation, the countries with nuclear reactors can be eliminated, too. Table A1 shows that 21 countries have no nuclear power plants for industrial uses except for the research. Of all 21 countries, 19 units are from the donor pool and Estonia and Luxembourg are added from the out of samples.

Table A1: The History of the 21 Control Units without Nuclear Power Plants

Country	Notes for Nuclear Energy
Australia	• No nuclear facilities • The country is the third largest uranium producer
Austria	• Austrian government started nuclear energy program in 1960. The government approved an anti-nuclear bill in 1997.
Chile	The technical study started in 2007
Estonia	• The Estonian government approved the construction of nuclear power plant in 2011. • The first nuclear power plant is built by 2023.
Greece	• Only one research reactor is located.
Iceland	• Hydro and geothermal power plants are located

Ireland	• The republic of Ireland has no nuclear power plant but it has the electric grid connected with the island of Great Britain.
Israel	• The country considered the needs for nuclear power plant in 2007. • In 2015 the government believed that the first nuclear plant is built for the GHG emission reduction.
Italy	• The country started the electricity from nuclear energy in 1960 and all reactors are shut down by 1990.
Luxembourg	• The opposition to construct nuclear power plant was passed in 1977.
New Zealand	• Nuclear powered facility is prohibited by the prime minister in 1984.
Norway	• Not any nuclear power plant is located in the country but there are four research reactors.
Poland	• The country plans to construct the nuclear power plant in 2025.
Portugal	• 1 MW research reactor is located in the country.
Turkey	• The first nuclear plant is expected to start the construction in 2018
Colombia	• Colombia has no nuclear plants and monitors the nuclear development around the country with the nuclear security center.
Costa Rica	• The country consumes 90% of electricity from water and wind sources.
Indonesia	• According to presidential decree, the country has a plan to build the nuclear plant by 2025.
Croatia	• Croatia has no nuclear power plants in the country but co-owned the plant with Slovenia.
Cyprus	• The country did not produce any nuclear power energy.
Latvia	• The first research reactor was constructed in 1959 when the country was one of the satellite countries in the USSR. • After the collapse of the USSR, the country has no more nuclear power plant.

Source: Summarized by the author using the national agency of energy of each country

Table A2: Pre-Intervention Characteristics (Countries with Nuclear Plants Excluded)

		Japan	Synthetic Japan
GHG emission per capita [a]		9.816	9.782
Employment ratio by sectoral industry [b]	Agriculture & Fishery	4.463	4.817
	Mining	0.063	0.475
	Manufacture	18.364	18.218
	Utilities [c]	0.527	0.993
	Construction	9.146	8.998
	Services [d]	66.384	66.457
Non-medical determinants [e]	Total fat supply	88.745	131.667
	Total calories supply	2804.273	3338.388
	Total protein supply	92.291	102.859
	Sugar supply	28.745	37.869
	Vegetables supply	106.027	124.647
	Fruits supply	54.855	113.536
Population ratio [f]	15-64 years old population	66.743	67.167
	Over 65 years old population	19.102	15.603
GDP per capita		28.325	28.025
GDP growth rate [g]		0.382	2.997

Source: Computation from the data
[a] GHG emission per capita (thousand kilograms), average for 1995-2010
[b] Percentage of employed person in the industries over total employed population, 2002-2007
[c] Utility industries divide into electricity, gas, and water
[d] Services divide into real estate, life-related, entertainment, food & beverage, and technical service
[e] Each item has its own unit by yearly or daily consumption, average for 2000-2010
[f] Percentage over total population, 1995-2010
[g] Percentage change of GDP in annually, average for 1995-2010

Following assumptions of the SCM, the results from the analysis can show more reliable statistical significance. Only possible problem is the lack of the sample data.

Table A2 presents the predictors' characteristics of Japan and synthetic Japan. The values of each predictor is close to the treated unit.

Table A3: Weight for Each Control Unit (Countries with Nuclear Plants Excluded)

Country	Synthetic control	Country	Synthetic control
Australia	0.112	Norway	0.000
Austria	0.000	Poland	0.000
Chile	0.006	Portugal	0.001
Estonia	0.148	Turkey	0.000
Greece	0.000	Colombia	0.000
Iceland	0.000	Costa Rica	0.000
Ireland	0.079	Indonesia	0.000
Israel	0.000	Croatia	0.000
Italy	0.491	Cyprus	0.160
Luxembourg	0.000	Latvia	0.000
New Zealand	0.001		

Source: Computation from the data by SCM

Table A3 shows the weight of each country in the donor pool. The 8 countries contribute to construct the synthetic control unit: Australia (11.2%), Chile (0.6%), Estonia (14.8%), Ireland (7.9%), Italy (49.1%), New Zealand (0.1%), Portugal (0.1%), and Cyprus (16%). Figure A1 provides that trajectory of the GHG emission per capita in Japan and synthetic Japan. The divergence starts prior to the intervention year (2011) but the trend of synthetic control shows continuity. The gaps between the treated and the control unit presents no difference before the intervention. The two graphs of trajectory and the gaps implies per capita GHG emission is affected by the natural disaster.

Figure A3 to A6 presents the placebo studies with all 21 control units and the country with higher MSPE than Japan is excluded by the level of cut off. Figure A4 provides 18 countries without Australia (1.64), Estonia (0.60), and Luxembourg (22.8) presenting greater MSPE in the parentheses than the Japan. Figure A5 excludes Iceland (0.7), Ireland (1.7), and Poland (0.25). Figure A6 eliminates no control units because all 15 units from the previous placebo test show lower MSPE than Japan. The probability of a random permutation of the intervention is 1/15 = 0.066 and it has 94% statistical confidence.

Figure A7 shows the leave-one-out test of the 8 countries with positive weight in Table A3. All 8 control units present the same path way and it means the countries are not sensitive to the intervention. Figure A8 provides the ratio of post to pre period MSPE and the Japan stands out to the rest of the control unit. The probability of obtaining the ratio like the Japan is 1/21=0.047. It implies when any country randomly experience the intervention the probability of having the same ratio of the Japan is 4.7%. With the new 21 control units, the SCM shows statistically significant and robustness in the results.

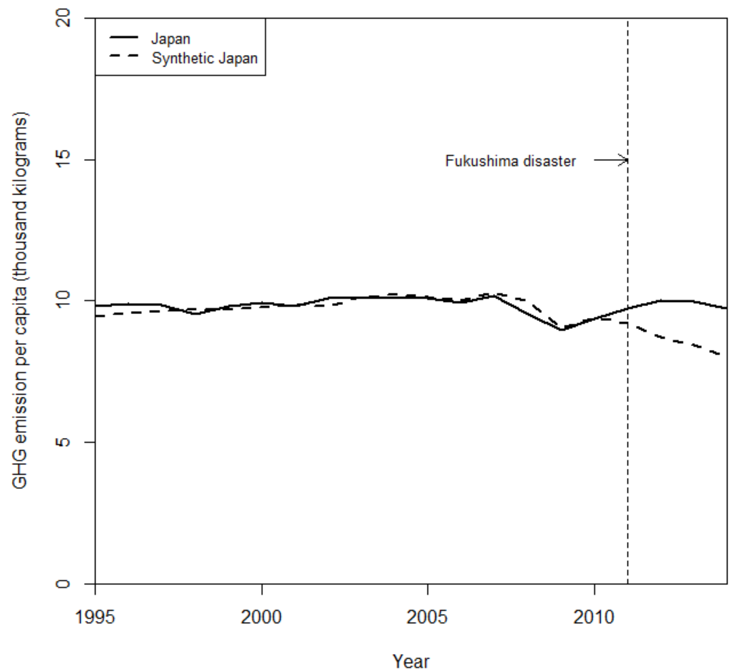

Figure A1: GHG Emission per capita of Treated and Synthetic Treated

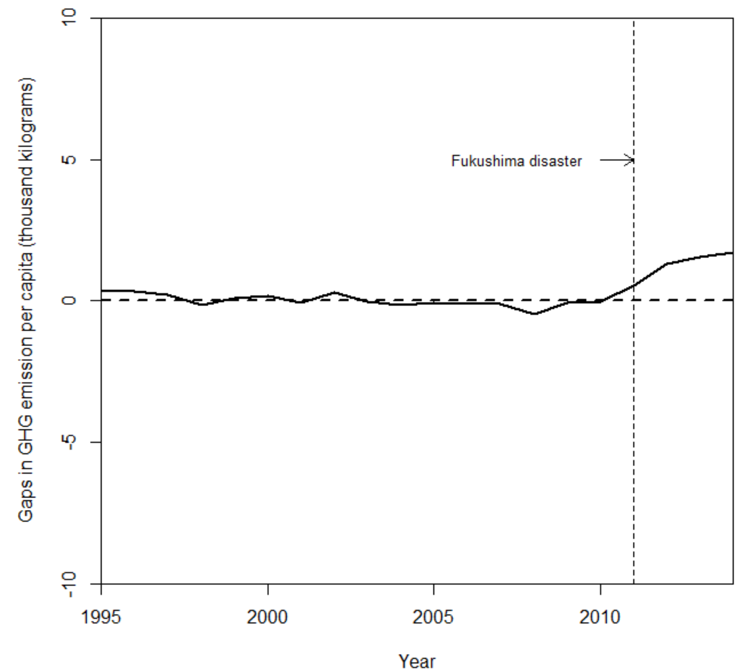

Figure A2: Gaps in GHG emission per capita of Treated

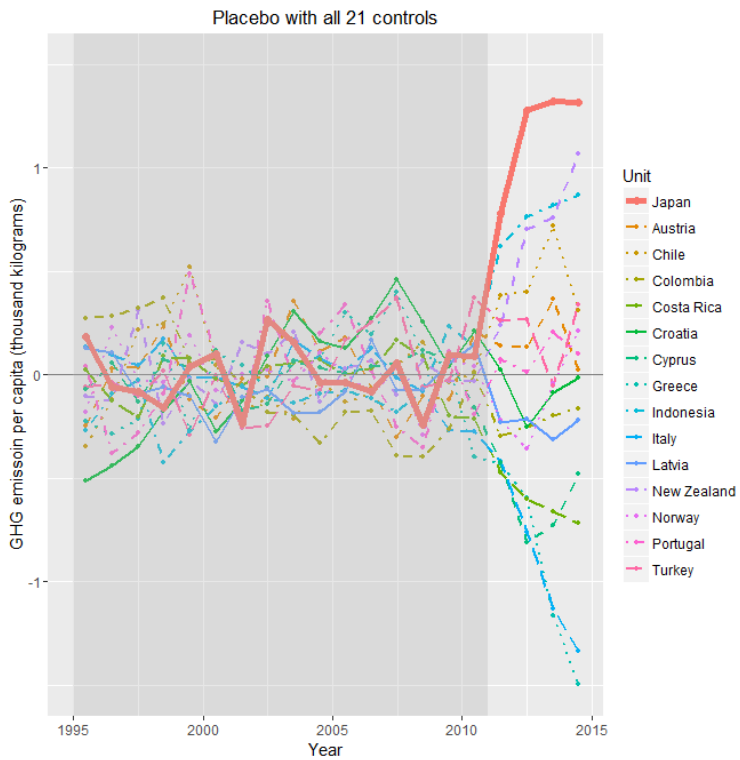

Figure A3: Placebo Studies with all 21 Control Countries

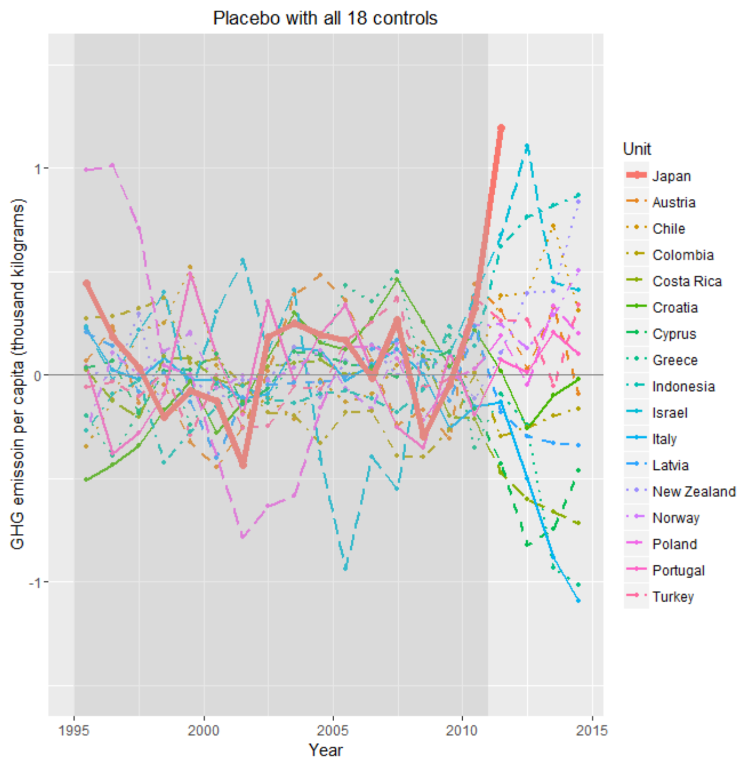

Figure A4: Placebo Studies with all 18 Control Countries

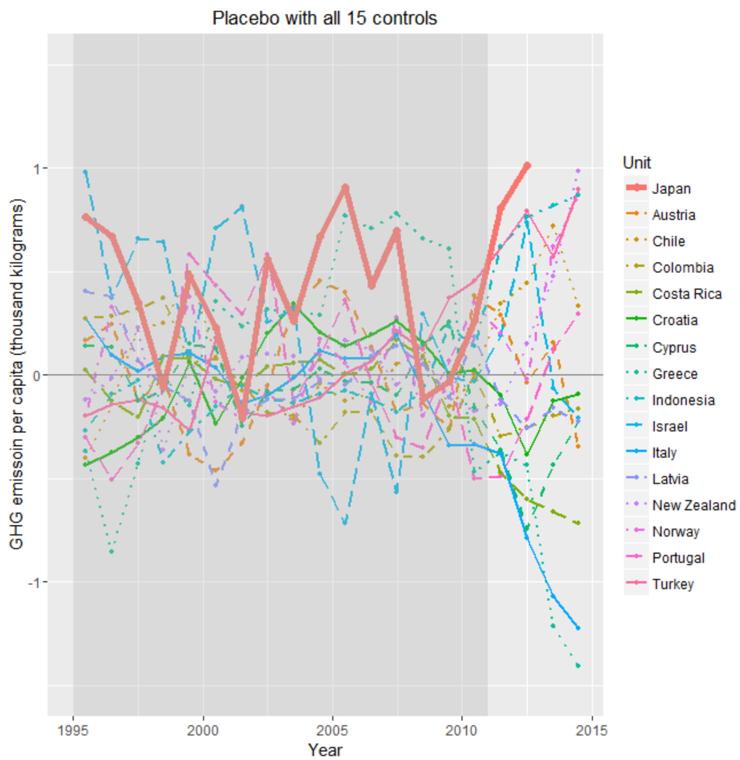

Figure A5: Placebo Studies with all 15 Control Countries

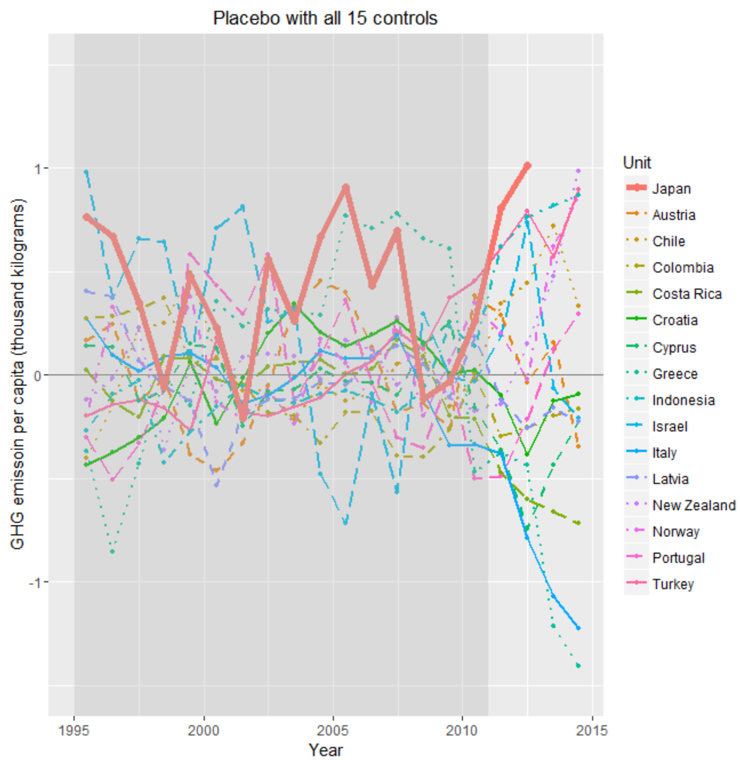

Figure A6: Placebo Studies with all 15 Control Countries (No Exclusion)

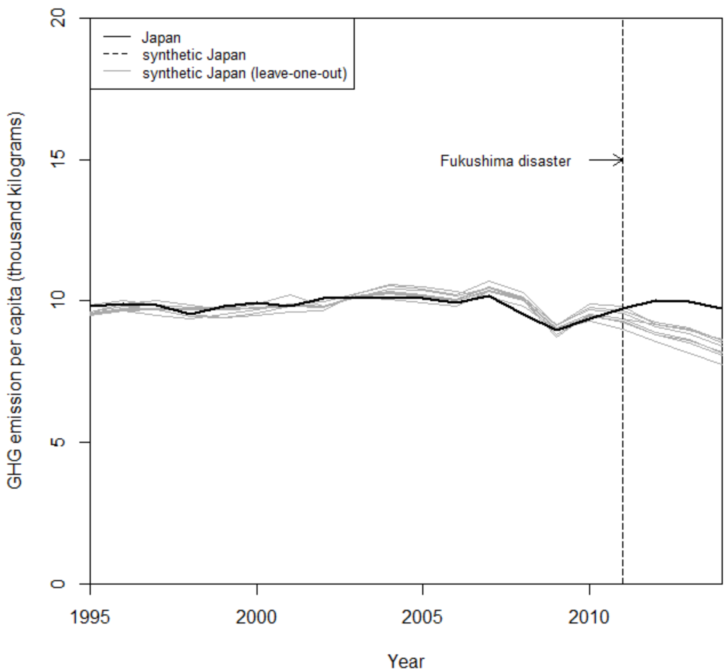

Figure A7: Leave-One-Out Distribution of the Synthetic Treated

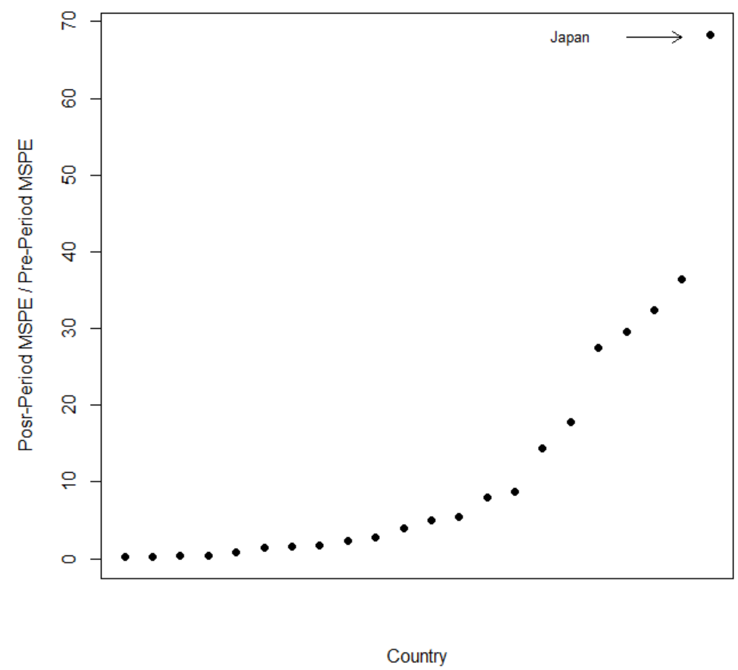

Figure A8: Post-Period MSPE / Pre-Period MSPE of Treated

Table A4: MSPE Ratio of Post-to-Pre-Intervention for Placebo studies

Country	MSPE ratio (Post/Pre)	Country	MSPE ratio (Post/Pre)
Japan	68.335	New Zealand	27.548
Australia	0.393	Norway	3.970
Austria	1.725	Poland	1.375
Chile	4.991	Portugal	0.226
Estonia	5.457	Turkey	1.636
Greece	14.398	Colombia	0.861
Iceland	2.284	Costa Rica	29.569
Ireland	8.664	Indonesia	17.832
Israel	2.703	Croatia	0.205
Italy	36.344	Cyprus	32.388
Luxembourg	0.429	Latvia	7.951

Source: Calculated by the package of ‘MSCMT’ in R