The Swiss case: Reactions of the real economy to the discontinuation of the exchange rate floor in 2015. A synthetic control approach *

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Preliminary – please do not quote

March 16, 2018

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1 The Synthetic Control Method

In this section I want to give a short description of the synthetic control method. It follows mainly Abadie, Diamond, and Hainmueller (2010). For details please refer to this paper and to Abadie, Diamond, and Hainmueller (2014) and Becker and Klößner (2018).

The synthetic control method is a data-driven approach to construct a suitable control unit in comparative case studies. The idea is that a combination of control units will often provide a better comparison for the treated unit than a single control unit alone. Therefore, the synthetic control is constructed as a weighted average of so called donors, a sample of suitable control units, with non-negative weights that sum to one. These weights, collected in a vector W, are calculated by minimizing the difference of selected predictor variables between the treated unit and the synthetic control. The predictor variables can be linear combinations of the outcome variable prior to treatment as well as other covariates with explanatory power for the outcome of interest, which need to be measured prior to or unaffected by the treatment. In the optimization the predictors are weighted by a predictor weighting matrix V, which is chosen to result in optimal weights W that yield the lowest possible RMSPE between the outcome of the treated unit and the synthetic control prior to treatment. This structure leads to a nested optimization problem. In the inner optimization the optimal donor weights W are determined, which construct the synthetic control unit. These optimization depends on the predictor weights V, which are determined in the outer optimization to guarantee the best possible pre-treatment fit. The resulting optimal weights define the synthetic control unit. The treatment effect consists of the difference in the outcome variable after treatment between the treated unit and the synthetic control.

2 Implementation

The structure of the synthetic control method described above poses some challenges to the implementation. The problem is that the nested optimization is not only computational intensive and therefore slow with larger data sets, but it might also be quite unstable and unreliable with numerical optimizers. The reason for that is that the objective function of the outer optimization contains a minimization problem, which results in a noisy function that might be ill behaved and can fool the outer optimizer. Becker and Klößner (2018) provide an algorithm that tries to reduce these problems. It starts with detecting important special cases that are easy to compute and then tries to reduce the dimension of the nested optimization problem.

The basis of Becker and Klößner's argumentation consists of some theory concerning the optimization problems that have to be solved for applying the synthetic control method. They start with separating the donor pool in sunny and shady donors. A shady donor is a control unit, whose difference in predictor values to the treated unit multiplied by α with $0 < \alpha < 1$ lies inside the convex hull of the differences of all donor units. They show that if a donor is shady, it will not be part of an optimal synthetic control unit. Furthermore, they give simple solutions in cases with no sunny donors, which means exact fit is possible, or only one sunny donor, which will then be the unique donor with positive weight. If none of these special cases occur, the algorithm tests whether the unrestricted outer optimum is feasible. This means it searches for predictor weights V which result in donor weights W that constitute the global minimum of the outer optimization problem. Only if finding such predictor weights is not possible, the nested optimization is performed. In order to do this, the dimension of the problem is reduced by excluding all shady donors. A detailed description of the algorithm can be found in Becker and Klößner (2018) and Figure 2 in their paper illustrate it's structure in a simple way.

I implement this algorithm in a python program. For optimizers and solvers to the linear programs I rely on the open source library scipy, which is used for scientific computation. During the implementation I had to make some design choices and I deviate from the algorithm at one place. This deviation occurs in the special case when no sunny donors are found, so that exact fit is possible. As the optimizers in scipy can not deal with situations with more equality constraints than independent variables, I choose to take a short cut there. In this case my program will only perform the inner minimization and print a warning. This will result in weights that lead to exact fit of the synthetic control regarding the predictors, but, if multiple such weights exist, it might choose a suboptimal solution regarding the outer optimization. In my opinion this is not major concern as this special case is very rare. The program will return a warning informing the user and suggesting to increase the number of predictor variables. The more predictors, the less likely it will become that exact fit is possible and that there are no sunny donors. In an extreme case all outcome variables defining the outer optimization could be chosen as predictors, which would render the problem unimportant as inner and outer optimization would coincide.

For the nested optimization I followed the algorithm closely. However, the suggested method for the inner optimization is not implemented in scipy. Instead I relied on sequential least squares programming to solve the inner minimization, as it can handle equality constraints and bounds for independent variables. This leads to the problem that the inner optimization is slower and much more noisy than in the implementation by Becker and Klößner. For the outer optimization I relied on the method L-BFGS-B, as routines using this algorithm performed quite well in their tests. Nevertheless, this combination of optimizers still lead to a quite unstable nested optimization. In some, more complex cases the outer optimizer is not capable of handling the noisy and sometimes ill behaved inner objective function. This did not change when I used other outer optimizers in scipy capable of box constrained minimization.

3 Appendix

The programming code is available on request. The program is based on the template for economic programming by von Gaudecker (2014).

3.1 Tables

Table 1a: Weights specification 1: GDP per capita, baseline

Country	Sunny Donor	Weight
Australia	Yes	0.3862
Austria	Yes	0.1021
Belgium	Yes	0.0320
Canada	No	0.0000
Czech Republic	No	0.0000
Denmark	No	0.0000
Finland	Yes	0.0000
Hungary	No	0.0000
Iceland	Yes	0.0000
Luxembourg	Yes	0.1843
Netherlands	No	0.0000
New Zealand	Yes	0.0000
Norway	Yes	0.1366
Sweden	No	0.0000
United Kingdom	No	0.0000
United States	Yes	0.1589

Table 1b: Weights specification 2: GDP per capita, all year averages as predictors

Country	Sunny Donor	Weight
Australia	Yes	0.7012
Austria	Yes	0.0000
Belgium	Yes	0.0000
Canada	Yes	0.0000
Czech Republic	Yes	0.0000
Denmark	Yes	0.0000
Finland	Yes	0.0000
Hungary	Yes	0.0000
Iceland	Yes	0.0000
Luxembourg	Yes	0.2421
Netherlands	Yes	0.0000
New Zealand	Yes	0.0000
Norway	Yes	0.0567
Sweden	Yes	0.0000
United Kingdom	Yes	0.0000
United States	Yes	0.0000

Table 1c: Weights specification 3: GDP per capita, with covariates as predictors

Country	**Sunny Donor**	**Weight**
Australia	No	0.0000
Austria	No	0.0000
Belgium	Yes	0.0000
Canada	Yes	0.0460
Czech Republic	Yes	0.2050
Denmark	No	0.0000
Finland	No	0.0000
Hungary	Yes	0.0000
Iceland	No	0.0000
Luxembourg	Yes	0.1856
Netherlands	No	0.0000
New Zealand	Yes	0.0000
Norway	Yes	0.1818
Sweden	Yes	0.0000
United Kingdom	Yes	0.0000
United States	Yes	0.3818

Table 2a: Predictors specification 1: GDP per capita, baseline

predictor	**treated country**	**synthetic control**
GDPPC 2008	53743.67	53784.62
GDPPC 2010	52857.98	52799.27
GDPPC 2012	53432.64	53330.78
GDPPC 2013	53818.96	53600.88
GDPPC 2014	54465.20	54518.70

Table 2b: Predictors specification 2: GDP per capita, all year averages as predictors

predictor	**treated country**	**synthetic control**
GDPPC 2007	53268.45	53954.39
GDPPC 2008	53743.67	53433.02
GDPPC 2009	51916.30	51985.97
GDPPC 2010	52857.98	52785.30
GDPPC 2011	53487.37	53184.26
GDPPC 2012	53432.64	53277.67
GDPPC 2013	53818.96	53610.47
GDPPC 2014	54465.20	54624.97

Table 2c: Predictors specification 3: GDP per capita, with covariates as predictors

predictor	**treated country**	**synthetic control**
GDPPC 2012-2014	53905.60	53218.99
Trade Openness	124.11	124.29
Industry Share	26.33	26.33
Inflation Rate	-0.31	1.68
Schooling	84.18	84.16

Table 3: Weights for current account specification

Country	**Sunny Donor**	**Weight**
Australia	No	0.0000
Austria	No	0.0000
Belgium	Yes	0.0000
Czech Republic	Yes	0.0000
Denmark	Yes	0.1841
Finland	No	0.0000
Hungary	No	0.0000
Iceland	No	0.0000
Luxembourg	Yes	0.0126
Netherlands	Yes	0.5369
New Zealand	Yes	0.0000
Norway	Yes	0.2664
Sweden	Yes	0.0000
United Kingdom	No	0.0000
United States	Yes	0.0000

Table 4: Predictors for current account specification

predictor	**treated country**	**synthetic control**
Current Account 2012-2014	10.04	9.75
Trade Openness	124.11	124.24
Industry Share	26.33	26.44
Inflation Rate	-0.31	1.75
Schooling	84.18	72.45

Table 5a: Weights for time placebo specification

Country	**Sunny Donor**	**Weight**
Australia	Yes	0.0000
Austria	Yes	0.0000
Belgium	Yes	0.0000
Canada	No	0.0000
Czech Republic	Yes	0.0000
Denmark	Yes	0.5258
Finland	No	0.0000
Hungary	Yes	0.0000
Iceland	Yes	0.0000
Luxembourg	Yes	0.0000
Netherlands	Yes	0.0000
New Zealand	No	0.0000
Norway	Yes	0.4742
Sweden	No	0.0000
United Kingdom	Yes	0.0000
United States	Yes	0.0000

Table 5b: Weights for country placebo specification

Country	**Sunny Donor**	**Weight**
Austria	Yes	0.0000
Belgium	Yes	0.0000
Canada	Yes	0.0000
Czech Republic	Yes	0.0000
Denmark	No	0.0000
Finland	Yes	0.0000
Hungary	Yes	0.0000
Iceland	Yes	0.0000
Luxembourg	Yes	0.0000
Netherlands	No	0.0000
New Zealand	Yes	0.4333
Norway	Yes	0.0000
Sweden	Yes	0.0000
United Kingdom	No	0.0000
United States	Yes	0.5667

Table 6a: Predictors for time placebo specification

predictor	**treated country**	**synthetic control**
GDPPC 1998	45746.97	45183.40
GDPPC 2000	47887.29	47384.66
GDPPC 2002	48027.82	48137.26
GDPPC 2003	47706.01	48269.82
GDPPC 2004	48633.56	49688.20

Table 6b: Predictors for country placebo specification

predictor	**treated country**	**synthetic control**
GDPPC 2008	40771.12	41323.76
GDPPC 2010	41048.33	40789.36
GDPPC 2012	42422.53	41847.80
GDPPC 2013	42595.93	42305.71
GDPPC 2014	43044.74	43048.59

3.2 Figures

Figure 1: 10 year EUR/CHF exchange rate 31.01.2008 to 01.02.2018, source: ECB, 01.02.2018

Figure 2a: Specification 1 (baseline): GDP per capita Switzerland and synthetic control

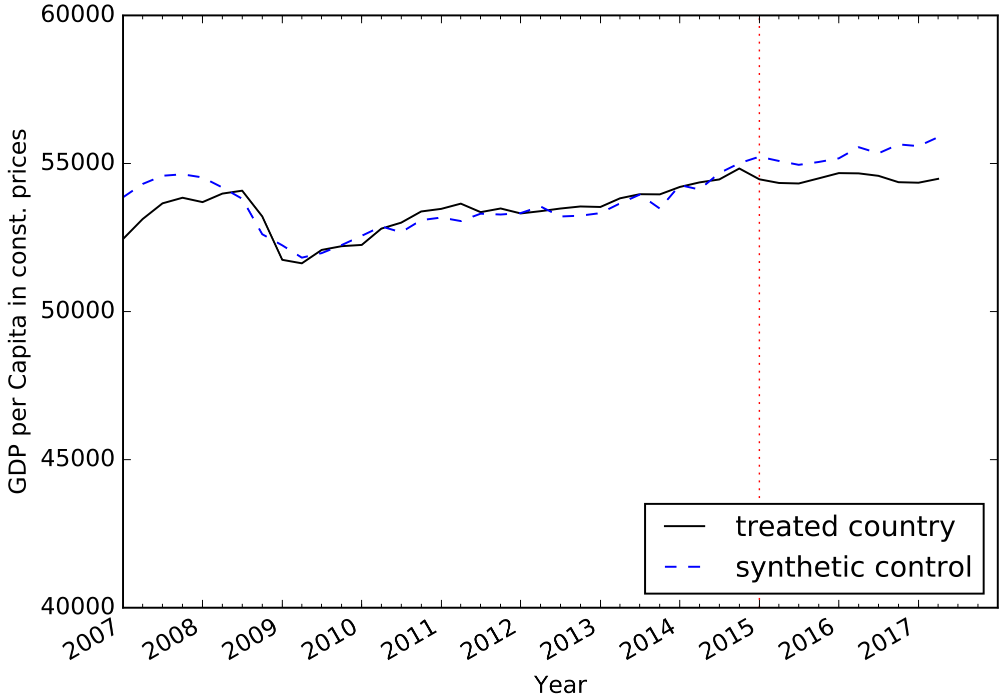


Figure 2b: Specification 2 (all year averages): GDP per capita Switzerland and synthetic control

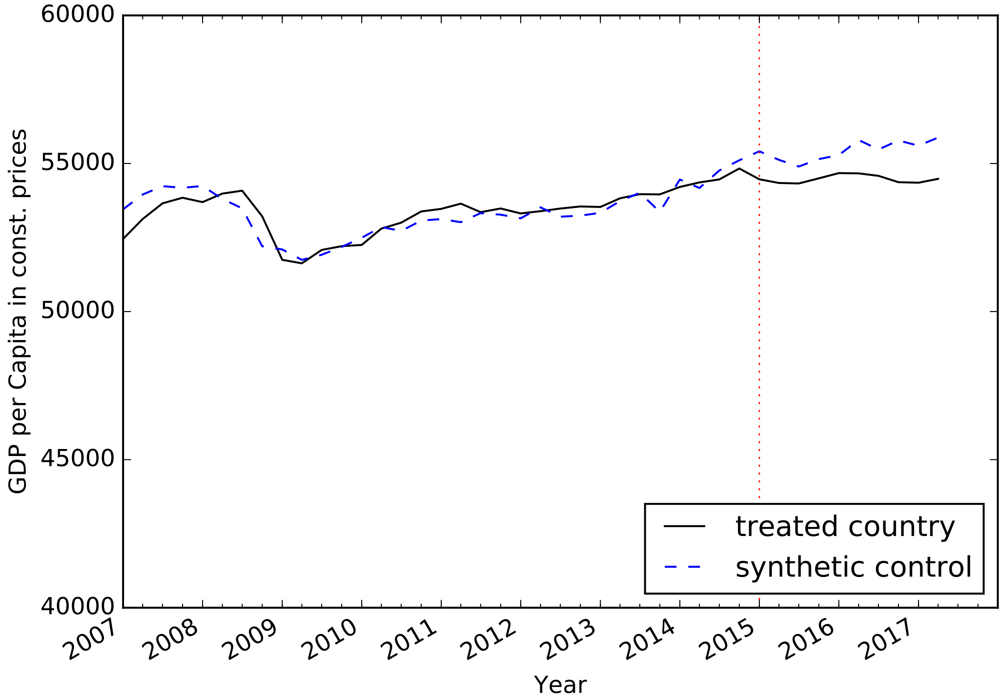


Figure 2c: Specification 3 (including covariates): GDP per capita Switzerland and synthetic control

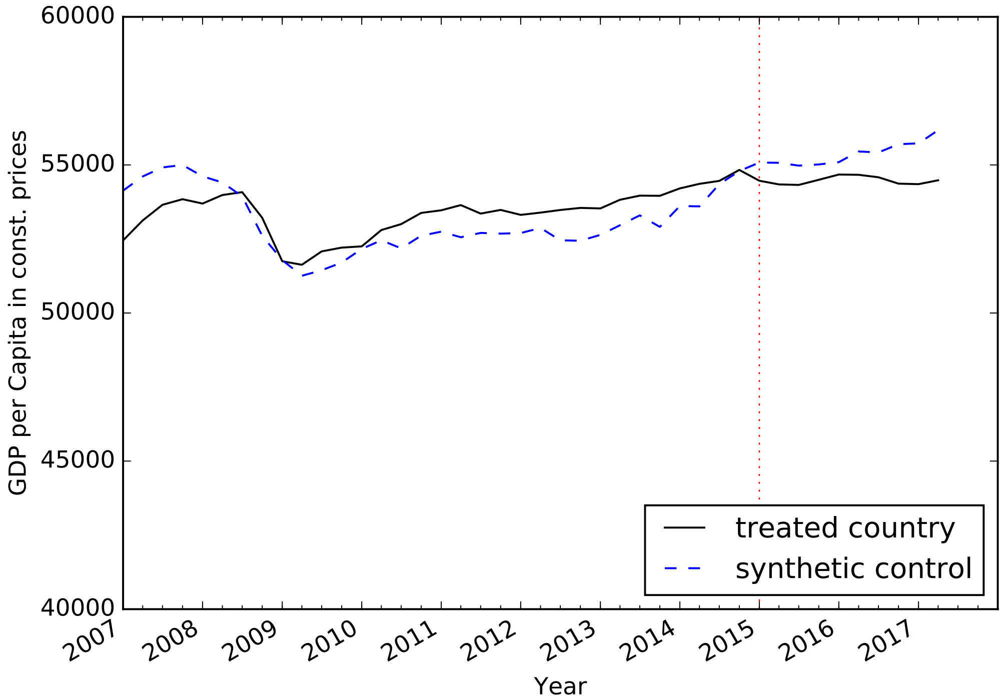


Figure 3: Current account in % of GDP Switzerland and synthetic control

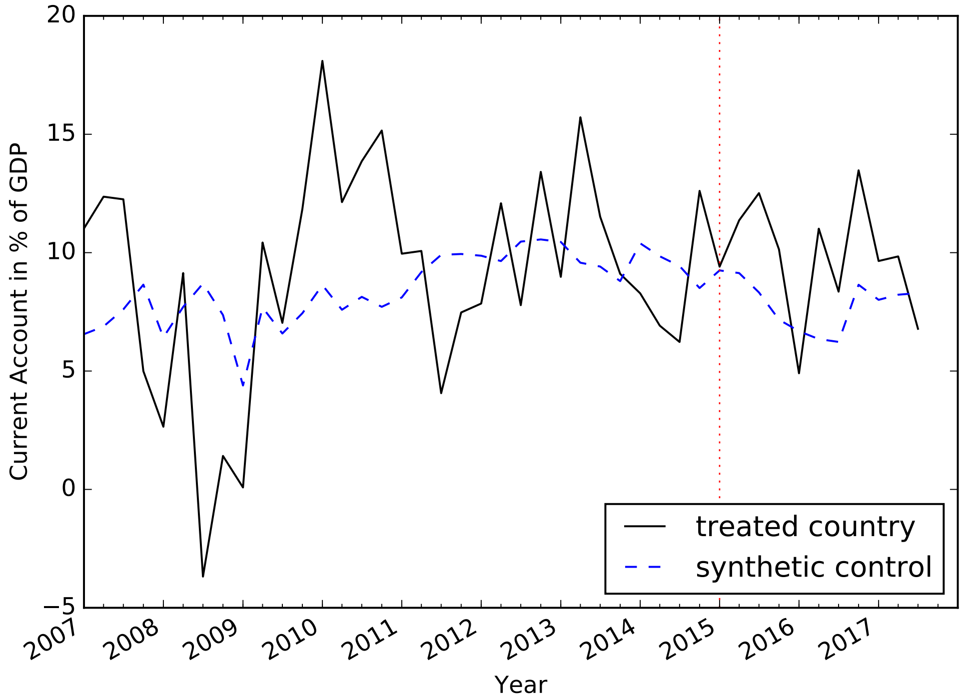


Figure 4a: Time Placebo (1997-2007Q2): GDP per capita Switzerland and synthetic control

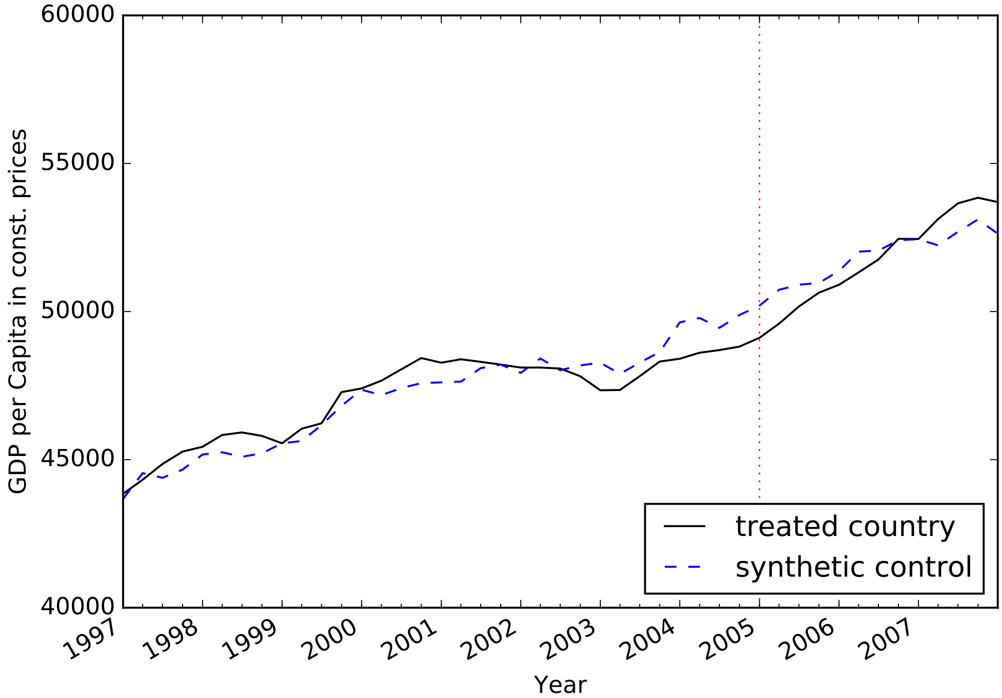
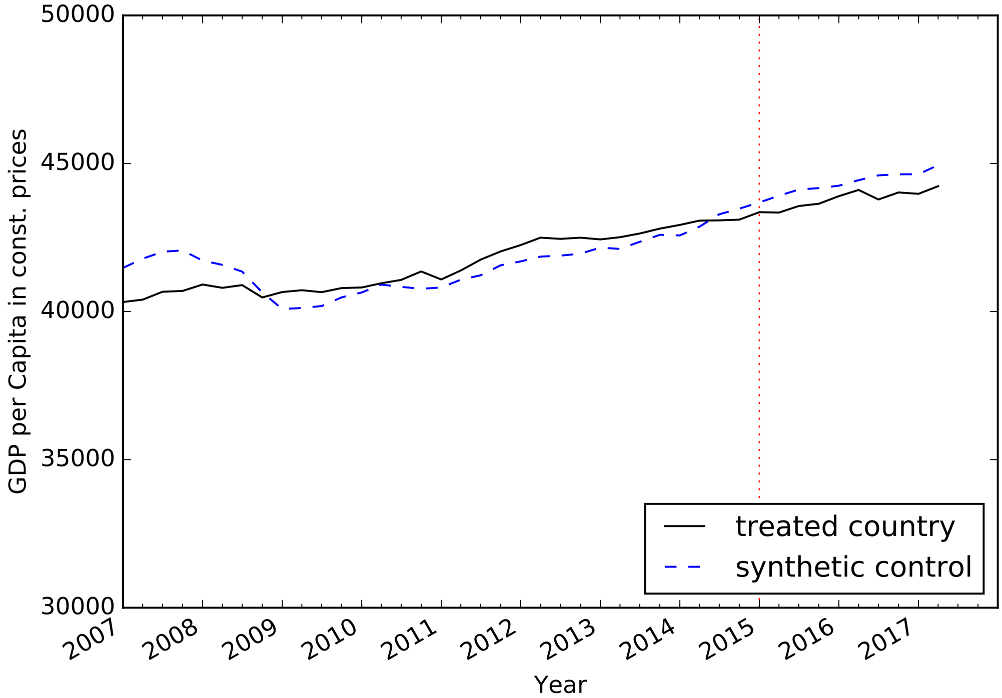


Figure 4b: Country Placebo: GDP per capita Australia and synthetic control



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