allsynth: Synthetic Control Bias-Correction Utilities for Stata

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allsynth is built on the synth package and adds functionality

In this presentation:

- Review of synthetic control methodology, including proposed bias-correction for inexact matching (Abadie and L'hour, 2020)
- Describe the functionality added by the allsynth package (with examples!):
 - Synthetic control bias-correction for inexact matching on predictor values
 - Calculation of RMPSE-ranked *p*-values from in-space treatment permutations
 - Expanded graphing functionality
 - Diagnostics for whether $\hat{\boldsymbol{W}}\text{-weighting matrix}$ is likely unique
- Examples rely on synth_smoking data from synth package (Abadie et al., 2010)

Canonical:

• Abadie & Gardeazabal, 2003; Abadie et al., 2010, 2015

Many treated units:

• Cavallo et al., 2013; Dube & Zipperer, 2015; Acemoglu et al., 2016; Abadie & L'Hour, 2020; Abadie, 2021; Ben-Michael et al., 2021b; Wiltshire, 2021a

Inference:

 Abadie et al., 2010, 2015; Doudchenko & Imbens, 2016; Hahn & Shi, 2017; Ferman & Pinto, 2017; Firpo & Possebom, 2018; Chernozhukov et al., 2019

Bias-correction for inexact matching on predictor values:

• Abadie & L'Hour, 2020; Abadie, 2021; Ben-Michael et al., 2021a; Wiltshire, 2021a

Abadie (2021) provides an excellent, current review

Potential outcomes framework

For any unit j at time t:

- Let $Y_{j,t}^{I}$ be the potential outcome under Intervention/treatment
- Let $Y_{i,t}^N$ be the potential outcome under Non-intervention/non-treatment
- The observed outcome is: $Y_{j,t} = Y_{j,t}^N + \tau_{j,t}D_{j,t}$
 - $\rightarrow D_{j,t}$ is a dummy indicating if j is treated at t
- Define the treatment effect in $\{j, t\}$ as: $\tau_{j,t} = Y_{j,t}^I Y_{j,t}^N$
- Let a single unit, j=1, become treated at \mathcal{T}_0+1
- We want to estimate path of treatment effects: $(au_{1, au_{0}+1},..., au_{1, au})$
- We can never observe both $Y_{1,t}^{\prime}$ and $Y_{1,t}^{N}$
- For $t > T_0$, $Y_{1,t} = Y_{1,t}^{\prime}$ is observable so we only need to estimate $Y_{1,t}^{N}$

Suppose we have data on J units over T periods

- j = 1 is a treated unit. j = 2, ..., J + 1 are untreated "donor pool" units
- T_0 pre-treatment periods, $T T_0 > 0$ treated periods
- We specify r covariates plus M linear combinations of $Y_{j,t}$ (for $t \leq T_0$) $\rightarrow r + M = K$ total predictor variables
- \mathbf{X}_1 is a $K \times 1$ vector of predictors of $Y_{1,t}$ in treated unit j = 1
- \mathbf{X}_0 is a $K \times J$ matrix of predictors of $Y_{j,t}$ in donor pool units j > 1

Synthetic control estimator with a single treated unit

Synthetic control estimator identifies a weighted average of donor pool units:

$$\hat{Y}_{1,t}^{N} = \sum_{j=2}^{J+1} \hat{w}_j Y_{j,t} \quad \forall \quad t$$

 \rightarrow Once we have $\hat{Y}_{1,t}^{\textit{N}}$, we can calculate: $\hat{\tau}_{j,t}=Y_{j,t}-\hat{Y}_{j,t}^{\textit{N}}$

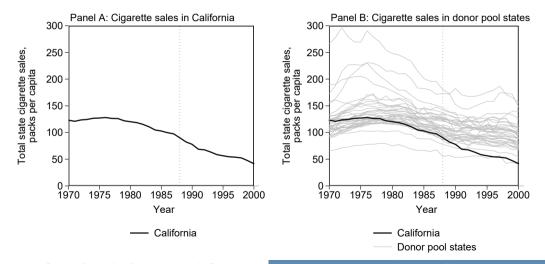
- $\mathbf{V} = (v_1, ..., v_K)$ is a matrix of weights on the predictor variables
- $W(V) = (w_2(V), \dots, w_{J+1}(V))'$ is a vector of weights on donor pool units j > 1
- Classic synthetic control selects \hat{V} and $\hat{W} = W(\hat{V})$ to minimize:

$$\left(\sum_{k=1}^{K} \hat{v}_k (X_{k,1} - w_2 X_{k,2} - ... - w_{J+1} X_{k,J+1})^2\right)^{1/2}$$

s.t. $\sum_{j=2}^{J+1} w_j = 1, w_j \ge 0 \quad \forall j \in \{2, ..., J+1\}$

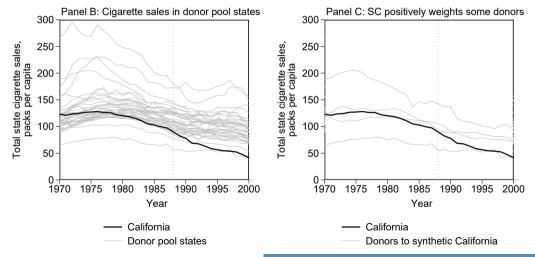
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Example: We observe cigarette sales in California and untreated states (donor pool). In 1989, California increased its cigarette excise tax



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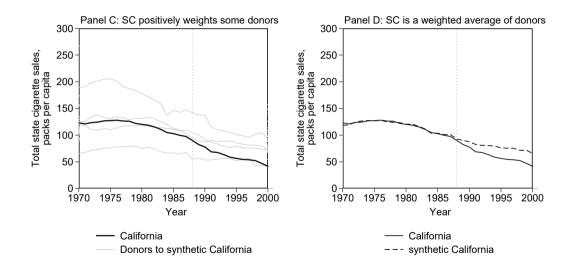
Synthetic control weights predictor variables, then positively weights some untreated states to best match pre-treatment California on those predictors



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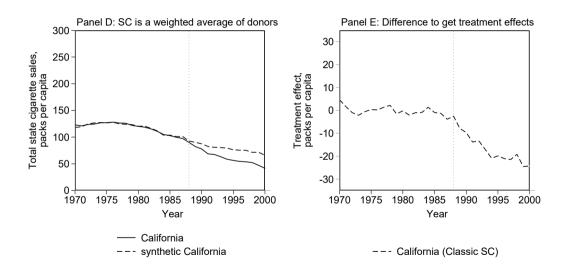
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The weighted average of those donors is the synthetic California



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California minus synthetic California cig sales is estimated treatment effect



The allsynth package: adds functionality to the synth package

- Synthetic control bias-correction for inexact matching on predictor values between a treated unit and its synthetic control donors (OLS regression)
- Automated calculation of RMPSE *p*-values from in-space permutation tests
- Expanded graphing functionality
- Uniqueness diagnostics (e.g. warns if the \hat{W} matrix is unlikely unique)

Note: In addition to directly utilizing the synth package, the code for allsynth draws appreciatively on Jens Hainmueller's code for synth and slightly on the code for synth_runner (Galiani and Quistorff, 2018).

• Abadie and L'Hour (2020) (independently, Ben-Michael et al. (2021a)) propose bias correction analagous to Abadie and Imbens (2011) for matching estimators

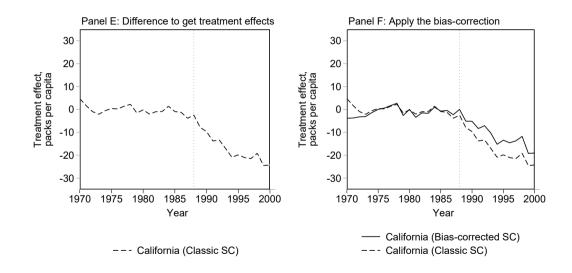
 $\rightarrow\,$ Wrote package to implement this in R

Bias correction for inexact matching on predictors (single treated unit)

- First get \hat{w}_i from synthetic control estimation on uncorrected values
- Let $\mu_{0,t}(x) = E[Y|X = x, D = 0]$, and let $\hat{\mu}_{0,t}(x)$ be an estimator of $\mu_{0,t}(x)$
- Estimate µ̂_{0,t}(x) by regressing Y_{j,t} for untreated j > 1, in each t ≤ T, on the predictor values, X₀, for untreated j > 1
- The bias in $\hat{\tau}_{1,t}$ from inexact matching is $\sum_{j=2}^{J+1} \hat{w}_j \hat{\mu}_{0,t}(X_j) \hat{\mu}_{0,t}(X_1)$
- Then the bias-corrected treatment effect at time t is:

$$\begin{split} \tilde{\hat{\tau}}_{1,t} &= \hat{\tau}_{1,t} - bias_t \\ &= (Y_{j,t} - \sum_{j=2}^{J+1} \hat{w}_j Y_{j,t}) - (\sum_{j=2}^{J+1} \hat{w}_j \hat{\mu}_{0,t}(\mathbf{X}_j) - \hat{\mu}_{0,t}(\mathbf{X}_1)) \\ &= (Y_{1,t} - \hat{\mu}_{0,t}(\mathbf{X}_1)) - \sum_{j=2}^{J+1} \hat{w}_j (Y_{j,t} - \hat{\mu}_{0,t}(\mathbf{X}_j)) \end{split}$$

Applying bias-correction to the California cigarette sales $\hat{\tau}_{1,t}$



allsynth can be used like synth but offers additional functionality

allsynth requires same specifications as synth. In addition, users may specify:

- bcorrect(string)
 - One of nosave, merge, or replace must be specified with <u>bcor</u>rect()
 - $\rightarrow \hat{\mu}_{0,t}(x)$ is estimated using OLS regression
 - $\rightarrow\,$ Requires at least K+2 donor pool units, K is # of predictors
 - figure may additionally be specified. e.g. bcorrect(replace figure)
- pvalues calculates RMPSE-ranked *p*-values from in-space placebo runs
 - If specified with bcorrect(), calculates classic and bias-corrected p-values
- placeboskeep saves the results of the placebo runs estimated for pvalues
 - May only be specified when both keep() and pvalues are also specified
- gapfigure(string)
 - One of classic, bcorrect, or placebos must be specified with gapfig()
 - At most two may be specified together
 - lineback may additionally be specified. e.g. gapfig(bcorrect lineback)
- \bullet allsynth will always warn if the \hat{W} matrix unlikely unique

Same primary specification as in the synth help file yields same results:

```
#delimit ;
   allsynth
    cigsale beer(1984(1)1988) lnincome retprice age15to24
    cigsale(1988) cigsale(1980) cigsale(1975),
    trunit(3) trperiod(1989)
   #delimit cr
```

allsynth: Can be used like synth

Also lets you know that you haven't properly specified bias-correction:

Louisiana	0
Maine	0
Minnesota	0
Mississippi	0
Missouri	0
Montana	0
Nebraska	0
Nevada	.245
New Hampshire	0
New Mexico	0
North Carolina	0
North Dakota	0
Ohio	0
Oklahoma	0
Pennsylvania	0
Rhode Island	0
South Carolina	0
South Dakota	0
Tennessee	0
Texas	0
Utah	.369
Vermont	0
Virginia	0
West Virginia	0
Wisconsin	0
Wyoming	0

Predictor Balance:

	Treated	Synthetic
beer(1984(1)1988) 24.28	23.22596
lnincom	e 10.03176	9.867266
retpric	e 66.63684	65.40743
age15to2	4 .1786624	.1825559
cigsale (1988	90.1	92.6063
cigsale (1980) 120.2	120.3907
cigsale (1975) 127.1	126.7094

Plain vanilla -synth- estimates provided. No bias correction or p-value calculations specified or applied If boorrect() was specified but no option was input inside the parentheses, bias-correction was not applied. > boorrect() must contain one of -noswer-, -merger, or -replace for bias-correction to be applied

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e.g. If we specify too few predictor variables, we get a warning message:

```
#delimit ;
    allsynth
    cigsale beer retprice cigsale(1980),
    trunit(3) trperiod(1989)
    #delimit cr
```

Warning: the -synth- weighting matrix W for treated unit (state == 3) contains more non-zero weights > than predictor variables and is likely not unique. Consider adding predictor variables

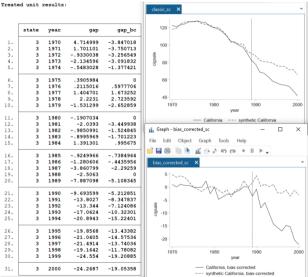
 \rightarrow

Add keep(smokingresults) replace figure bcorrect(replace figure):

#delimit ;
 allsynth
 cigsale beer(1984(1)1988) lnincome retprice age15to24
 cigsale(1988) cigsale(1980) cigsale(1975),
 trunit(3) trperiod(1989)
 keep(smokingresults) replace figure
 bcor(replace figure)
 #delimit cr

The bias-corrected outcome values are only useful to calculate the bias-corrected gaps!

allsynth: Can calculate, display, and save classic & bias-corrected "gaps"



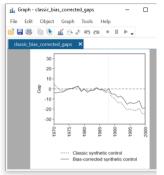
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Also add gapfig(classic bcorrect lineback). Drop fig and bcor(figure):
#delimit ;
 allsynth
 cigsale beer(1984(1)1988) lnincome retprice age15to24
 cigsale(1988) cigsale(1980) cigsale(1975),
 trunit(3) trperiod(1989)
 keep(smokingresults) replace
 bcorrect(replace) gapfig(classic bcorrect lineback)
 #delimit cr

allsynth: Can generate nice graphs of the classic and bias-corrected gaps

	state	year	gap	gap_bc
1.	3	1970	4.714999	-3.847018
2.	3	1971	1.701101	-3.750713
3.	3	1972	9330038	-3.256549
4.	3	1973	-2.134596	-3.091832
5.	3	1974	5483028	-1.377421
6.	3	1975	.3905984	0
7.	3	1976	.2115016	.5977706
8.	3	1977	1.404701	1.673252
9.	3	1978	2.2231	2.723592
10.	3	1979	-1.531299	-2.652859
11.	3	1980	1907034	0
12.	3	1981	-2.0393	-3,449938
13.	3	1982	9850991	-1.524845
14.	3	1983	8995969	-1.701223
15.	3	1984	1.391301	.995675
16.	3	1985	9249966	7384964
17.	3	1986	-1,280606	4435956
18.	3	1987	-3.860799	-2.29259
19.	3	1988	-2.5063	0
20.	3	1989	-7.887098	-5.108345
21.	3	1990	-9.693599	-5.212851
22.	3	1991	-13.8027	-8.347837
23.	3	1992	-13.344	-7.124086
24.	3	1993	-17.0624	-10.32301
25.	3	1994	-20.8943	-15.22401
26.	3	1995	-19.8568	-13.43382
27.	3	1996	-21.0405	-14.57536
28.	3	1997	-21.4914	-13.74036
29.	3	1998	-19.1642	-11.78082
30.	3	1999	-24.554	-19.20885
31.	3	2000	-24.2687	-19.05358



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allsynth: Can run placebo tests, calculate *p*-values, and graph permutation distributions

Instead add gapfig(bcorrect placebos lineback) pvalues placeboskeep:

#delimit ;

```
allsynth
  cigsale beer(1984(1)1988) lnincome retprice age15to24
  cigsale(1988) cigsale(1980) cigsale(1975),
  trunit(3) trperiod(1989)
  bcor(replace figure) gapfig(bcorrect placebos lineback)
  pval plac keep(smokingresults) rep
#delimit cr
```

allsynth: Can run placebo tests, calculate *p*-values, and graph permutation distributions



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Installing allsynth package for Stata: currently Version 0.0.7 BETA

In Stata, type:

```
net from https://justinwiltshire.com/s
net install allsynth, replace
help allsynth
```

There are nine examples in help file to teach the functionality of allsynth

Version 0.0.5 BETA contained a critical bug. Please update to the latest version

The allsynth package is a free contribution to the research community. Please cite it: **Wiltshire, Justin C**. 2021b. allsynth: Synthetic Control Bias-correction Utilities for Stata. Working paper.

Email comments and questions: jcwiltshire@ucdavis.edu

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