`allsynth`: Synthetic Control Bias-Correction Utilities for Stata

Justin C. Wiltshire

University of California, Davis

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I introduce a new community-contributed stata package: `allsynth`

`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 $\hat{\mathbf{W}}$-weighting matrix is likely unique
- Examples rely on synth_smoking data from `synth` package (Abadie et al., 2010)

Synthetic control literature

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

Synthetic control estimator with a single treated unit

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:

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

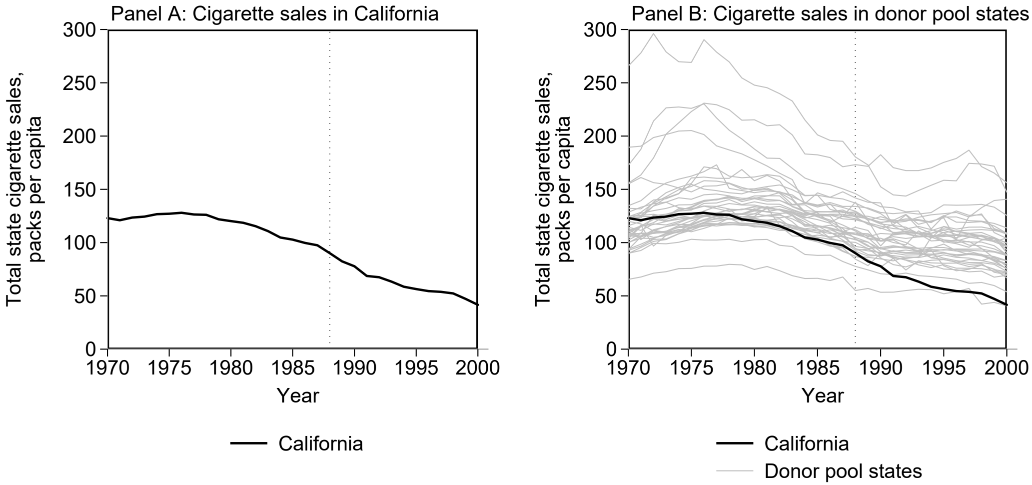
$\rightarrow$ Once we have $\hat{Y}^N_{1,t}$, we can calculate: $\hat{\tau}_{j,t} = Y_{j,t} - \hat{Y}^N_{j,t}$

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

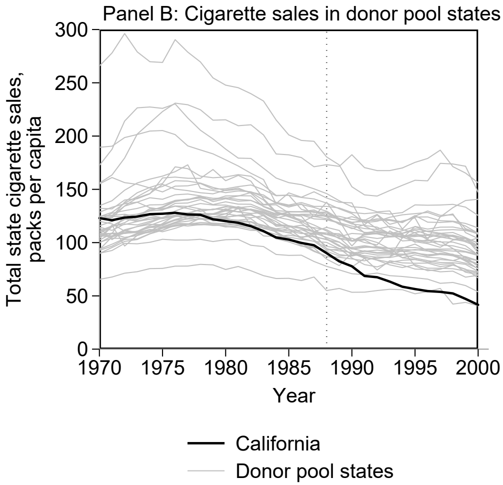
$$\left(\sum_{k=1}^{K} \hat{v}_k (X_{k,1} - w_2 X_{k,2} - ... - w_{J+1} X_{k,J+1})^2 \right)^{1/2}$$

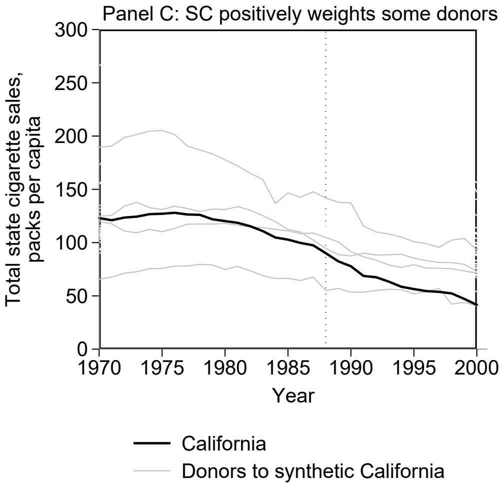
s.t. $\quad \sum_{j=2}^{J+1} w_j = 1, \ w_j \ \geq \ 0 \ \ \forall \ \ j \in \{2, ..., J+1\}$

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

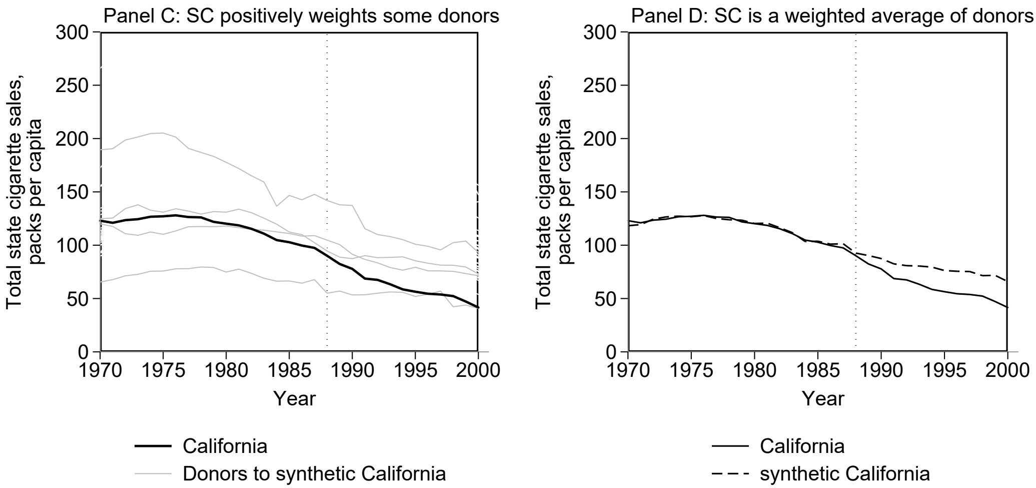


Synthetic control weights predictor variables, then positively weights some untreated states to best match pre-treatment California on those predictors

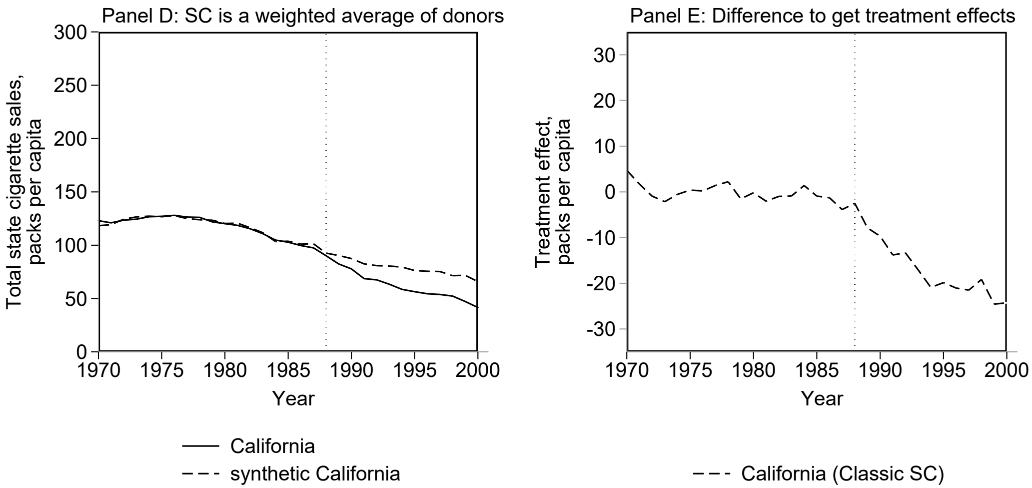




The weighted average of those donors is the synthetic California



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 $\hat{\mathbf{W}}$ 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).

Bias correction for inexact matching on predictor values

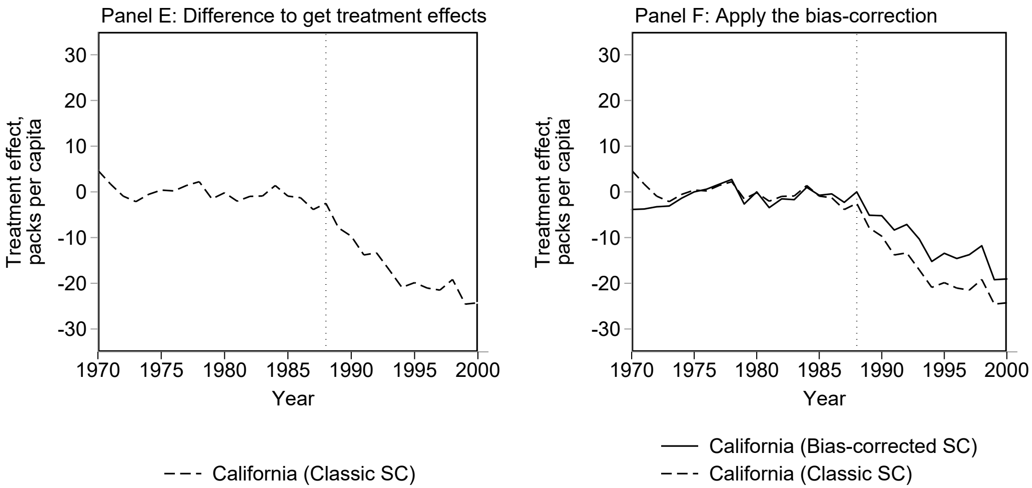
- Abadie and L'Hour (2020) (independently, Ben-Michael et al. (2021a)) propose bias correction analagous to Abadie and Imbens (2011) for matching estimators
  - $\rightarrow$ Wrote package to implement this in R

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

- First get $\hat{w}_j$ 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 $\hat{\mu}_{0,t}(x)$ by regressing $Y_{j,t}$ for untreated $j > 1$, in each $t \leq T$, on the predictor values, $\mathbf{X}_j$, for untreated $j > 1$
- The bias in $\hat{\tau}_{1,t}$ from inexact matching is $\sum_{j=2}^{J+1} \hat{w}_j(\hat{\mu}_{0,t}(\mathbf{X}_1) - \hat{\mu}_{0,t}(\mathbf{X}_j))$
- Then the bias-corrected treatment effect at time t is:

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

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 bcorrect()
    - → $\hat{\mu}_{0,t}(x)$ is estimated using OLS regression
    - → 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)
- allsynth will always warn if the $\hat{\mathbf{W}}$ matrix unlikely unique

`allsynth`: Can be used like `synth`

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:

Iowa	0
Kansas	0
Kentucky	0
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
lnincome	10.03176	9.867266
retprice	66.63684	65.40743
age15to24	.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.

allsynth: Cautions the user if the $\hat{\mathbf{W}}$ matrix is unlikely unique

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
```

$\rightarrow$

```
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
```

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

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

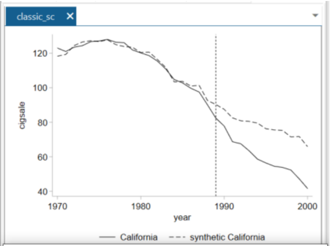
```
#delimit ;
    allsynth
      cigsale beer(1984(1)1988) lnincome retprice age15to24
      cigsale(1988) cigsale(1980) cigsale(1975),
      trunit(3) trperiod(1989)
      keep(smokingresults) replace figure
      bcor(replace figure)
    #delimit cr
```

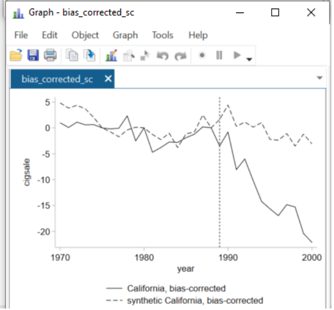
The bias-corrected outcome values are only useful to calculate the bias-corrected gaps!

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

Treated unit results:

	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





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

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
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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
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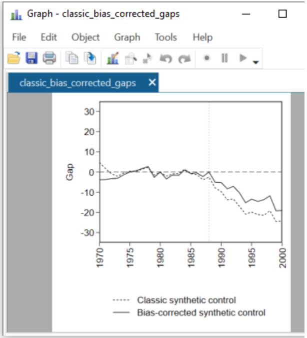
27.	3	1996	-21.0405	-14.57536
28.	3	1997	-21.4914	-13.74036
29.	3	1998	-19.1642	-11.78082
30.	3	1999	-24.554	-19.20885
31.	3	2000	-24.2687	-19.05358

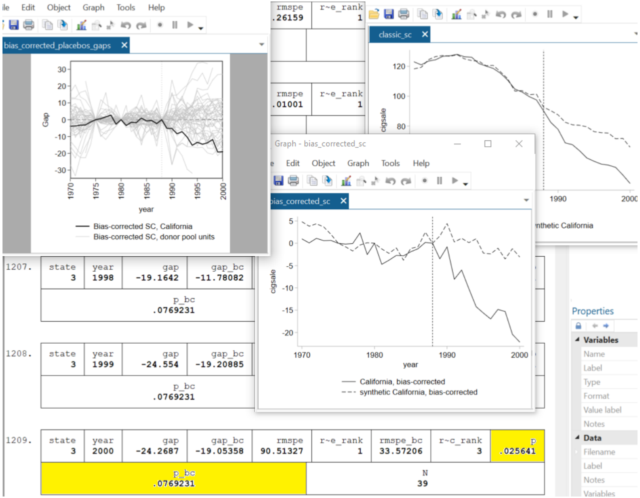


allsynth: Can run placebo tests, calculate *p*-values, and graph permutation distributions

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



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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Wiltshire, Justin C. 2021a. Walmart Supercenters and Monopsony Power: How a Large, Low-Wage Employer Impacts Local Labor Markets. *Working paper.*