The synth_runner Package: Utilities to Automate Synthetic Control Estimation Using synth

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Introduction

- Abadie and Gardeazabal (2003) and Abadie et al. (2010) introduced Synthetic Control Methods (SCM), to identifying treatment effects in case-studies.
- Abadie et al. (2010) released `synth` for Stata to perform a Synthetic Control estimation.
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Outline

Intuition

- Abadie and Gardeazabal (2003) and Abadie et al. (2010) introduced Synthetic Control Methods (SCM).
- Allows for estimating treatment effects even if treated unit is not on a parallel time trend as the mean of the untreated units.
- Constructs a counterfactual by finding a weighted average of non-treated units that resembles the treated unit in the pre-treatment period.

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DGP for Synthetic Controls

Synthetic Controls can be applied in multiple settings, but most common setting where there are theoretical results is:

- Units $\{1, ..., J+1\}$ with 1 being treated and J untread "donors". D_{jt} is the treatment indicator. T_0 pre-treatment periods and T total time periods. Factor Model:

$$Y_{jt} = \alpha_{jt} D_{jt} + Y_{jt}^N$$
$$Y_{jt} = \alpha_{jt} D_{jt} + (\theta_t' \mathbf{Z}_j + \delta_t + \lambda_t' \mu_j + \varepsilon_{jt})$$

  α_{jt} are time-varying treatment effects, Y_{jt}^N is the no-treated counterfactual, θ_t are unknown parameters, $\mathbf{Z}_j$ are observed unaffected covariates, δ_t is an unknown time factor, λ_t are unknown factors, μ_j are unknown factor loadings, and the error ε_{jt} is independent across units and time with zero mean.

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SC Estimator

- Let $\mathbf{W}$ be a weight vector over the other units such that $\mathbf{W} \geq \mathbf{0}$ and $\sum_j w_j = 1$.
- Split pre-/post-treatment Y as $(\overleftarrow{\mathbf{Y}} \backslash \overrightarrow{\mathbf{Y}})$.
- Let $\mathbf{Y}_0$ be the $(T \times J)$ matrix of outcomes for donors (similar for $\mathbf{Z}_0, \overleftarrow{\mathbf{Y}}, \overrightarrow{\mathbf{Y}}$).
- Suppose a $\mathbf{W}$ can be found such that the synthetic control matches the treated unit in pre-treatment:

$$\overleftarrow{\mathbf{Y}}_1 = \overleftarrow{\mathbf{Y}}_0 \mathbf{W}$$
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  and that $\sum_{t=1}^{T_0} \lambda_t \lambda_t'$ is non-singular.
- Estimate $\overrightarrow{\mathbf{Y}}_1^N$ as $\overrightarrow{\mathbf{Y}}_0 \mathbf{W}$ so $\hat{\alpha}_1 = \overrightarrow{\mathbf{Y}}_1 - \overrightarrow{\mathbf{Y}}_0 \mathbf{W}$
- Then $Bias(\hat{\alpha}) \to 0$ as T_0 grows large relative to ε_{it}.

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- Let "predictors" $\underleftarrow{\mathbf{X}}$ be comprised of $\mathbf{Z}$ and some linear combinations of $\overleftarrow{\mathbf{Y}}$.
- Define $\|\mathbf{A}\| = \sqrt{\mathbf{A}cols(\mathbf{A})^{-1}\mathbf{A}}$ and $\|\mathbf{A}\|_{\mathbf{V}} = \sqrt{\mathbf{A}\mathbf{V}^{-1}\mathbf{A}}$.
  - $\|\mathbf{Y}_1 - \mathbf{Y}_0\mathbf{W}\| = s_1$ is the root mean squared prediction error (RMSPE).
- As matching may only hold approximately, we need a set of predictor weights V that prioritizes which variables to match better.
- Given $\mathbf{V}$, then

$$\mathbf{W}^* = \arg\min_{\mathbf{W}} \|\mathbf{X}_1 - \mathbf{X}_0\mathbf{W}\|_{\mathbf{V}}$$

- Multiple options for $\mathbf{V}$ (`synth` includes regression weights and nested optimization $\mathbf{V}^* = \arg\min_{\mathbf{V}} \left\|\overleftarrow{\mathbf{Y}}_1 - \overleftarrow{\mathbf{Y}}_0\mathbf{W}(\mathbf{V})\right\|$)

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DGP II

- Factor model ($\lambda_t' \mu_j$) accommodates many forms:
  - Standard panel model with time and units fixed effects from $\mu_j = (1, \gamma_j)$ and $\lambda_t = (\xi_t, 1)'$
  - Unit-specific (non-parallel) time trends: $\mu_j = (\gamma_j)$ and $\lambda_t = (t)$
- Need $\sum_{t=1}^{T_0} \lambda_t \lambda_t'$ non-singular. Implies:
  - All factors must have been "active" in the past (one can not be all 0).
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Inference

- SCM relies on in-place placebo (permutation) tests for inference.
- Re-estimate synthetic controls on all J donors to get $\{\hat{\alpha}_p\}$. Call this the placebo distribution $\hat{\alpha}_1^{PL}$.
- Compare $\hat{\alpha}_1$ to $\hat{\alpha}_1^{PL}$. The two-sided p-value for $\hat{\alpha}_{1t}$ is then

$$p\text{-value} = \Pr\left(|\hat{\alpha}_{1t}^{PL}| \geq |\hat{\alpha}_{1t}|\right) = \frac{\sum_{j \neq 1} 1(|\hat{\alpha}_{jt}| \geq |\hat{\alpha}_{1t}|)}{J}$$

  the one-sided p-values (for positive effects) are

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Interpretation of Inference

- Interpretation is usually different than with randomization inference. Here it is "what proportion of untreated units have calculated effects as large?"
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Accounting for Match Quality

- Post-treatment differences may be large just because of poor match quality.
- Can take quality of match for pre-treatment period into account:
  - Limit donor pool to cases that matched as well as the treated unit was matched (limit by $\overleftarrow{s}_1$ or some multiple m of that).
  - Construct standardized (studentized) effects as in $\hat{\alpha}_1/\overleftarrow{s}_1$ and $\overrightarrow{s}_1/\overleftarrow{s}_1$.
- Inference can then be conducted over four quantities $(\hat{\alpha}_{jt}, \overrightarrow{s}_j, \hat{\alpha}_{jt}/\overleftarrow{s}_j, \overrightarrow{s}_j/\overleftarrow{s}_j)$ and the comparison set can also be limited by the choice of m.

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Multiple Treatments - Setup

- Cavallo et al. (2013) analyze multiple independent treatments at possibly different time periods.
- Index treated units $g \in \{1...G\}$. Let J be those units that never undergo treatment.
- Index effects relative to treatment date.

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- Index treated units $g \in \{1...G\}$. Let J be those units that never undergo treatment.
- Index effects relative to treatment date.

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Multiple Treatments - Estimation

For each $g \in \{1, ..., G\}$:

- Estimate vector $\hat{\alpha}_g$
- Estimate set of vectors $\hat{\alpha}_g^{PL} = \{\hat{\alpha}_j^g\}_{j \in J}$ assuming treatment date same as g
- (If two treated units have the same treatment period, then their placebo sets will the be the same.)

Define vector $\bar{\alpha} = G^{-1} \sum_{g \in G} \hat{\alpha}_g$

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Multiple Treatments - Estimation II

Defining $\bar{\alpha} = G^{-1} \sum_{g \in G} \hat{\alpha}_g$ smooths out noise in the estimate so one needs to do the same with the elements of the placebo set.

- Define an vector of choices from each placebo set $\tilde{j} = (j_1, ..., j_G)$ and the set of all such choices $\tilde{J}$.
  - $|\tilde{J}| = J^G$ unless limited by $\vec{s}$, in which case $\prod_{g=1}^{G} J_g$
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synth_runner Module

Abadie et al. (2010) introduce synth which conducts a single estimation. Building on that, synth_runner:

- Runs placebo tests and outputs p-values and confidence intervals
- Allows for matching on trends in the outcome variable rather than on the level
- Handles multiple-treatments
- Automates the process of splitting pre-treatment periods into "training" and "validation" sections
- Provides diagnostics
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Run estimation similar to ADH10

```
*Data setup the same for all examples
sysuse smoking
tsset state year

tempfile keepfile
*similar syntax to -synth-
synth_runner cigsale beer(1984(1)1988) lnincome(1972(1)
    1988) retprice age15to24 cigsale(1988) cigsale(1980)
    cigsale(1975), trunit(3) trperiod(1989) keep(`keepfile
    ')
```

Returned Values

Post-treatment joint significance

```
    e(pval_joint_post) = .1315789473684211
e(pval_joint_post_std) = 0
```

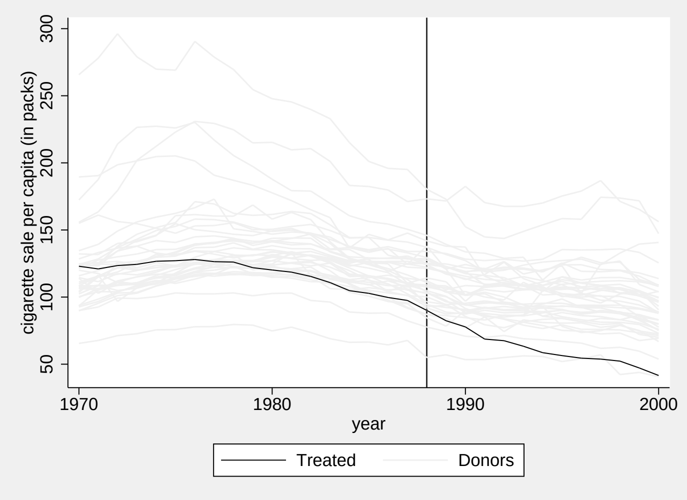
Diagnostics. If too small then SCM may not be appropriate for this unit. If conducting over multiple treatments, good to assess individual match quality and discard some units.

```
    e(avg_pre_rmspe_p) = .9210526315789474
```

Make Graphs

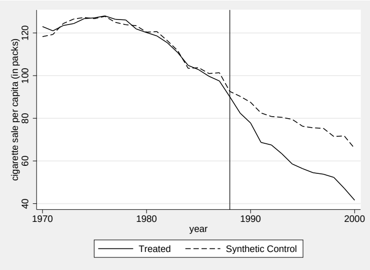
```
*`keepfile' now contains the differences between units and
     their synthetic controls
merge 1:1 state year using `keepfile', nogenerate
gen cigsale_synth = cigsale-effect
single_treatment_graphs, depvar(cigsale) trunit(3)
    trperiod(1989) effects_ylabels(-30(10)30) effects_ymax
    (35) effects_ymin(-35)
effect_graphs , depvar(cigsale) depvar_synth(cigsale_synth
    ) trunit(3) trperiod(1989) effect_var(effect)
pval_graphs
```

Outcome Trends

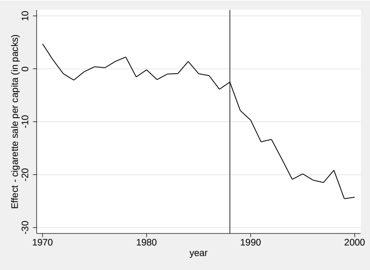


NB: Not a full test of parallel trends assumption as does not account for regression adjustment done in DiD.

Treated and Synthetic Control

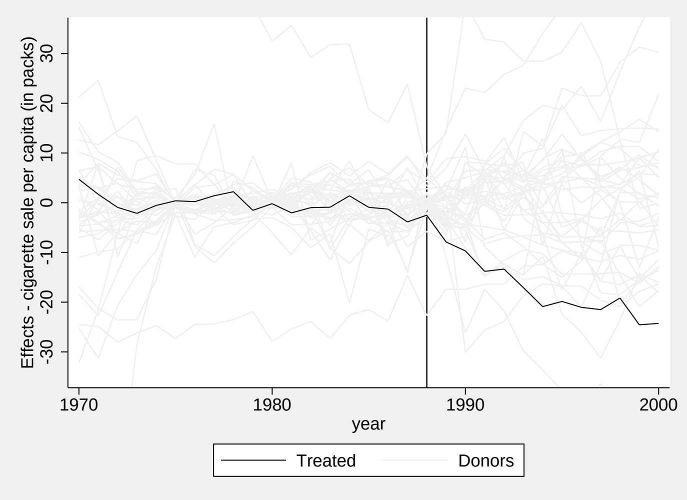


(a) Treated and Control

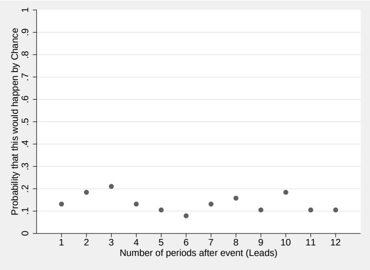


(b) Difference

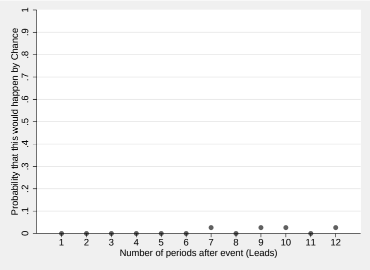
Differences



P-Values



(c) Effect



(d) Studentized Effect

More complicated example

```
gen byte D = (state==3 & year>=1989)
tempfile keepfile2
synth_runner cigsale beer(1984(1)1988) lnincome(1972(1)
    1988) retprice age15to24, trunit(3) trperiod(1989)
    trends training_propr(`=13/18') pre_limit_mult(10)
    keep(`keepfile2')
```

Returned Values

Post-treatment joint significance

```
    e(pval_joint_post) = .0263157894736842
e(pval_joint_post_std) = 0
```

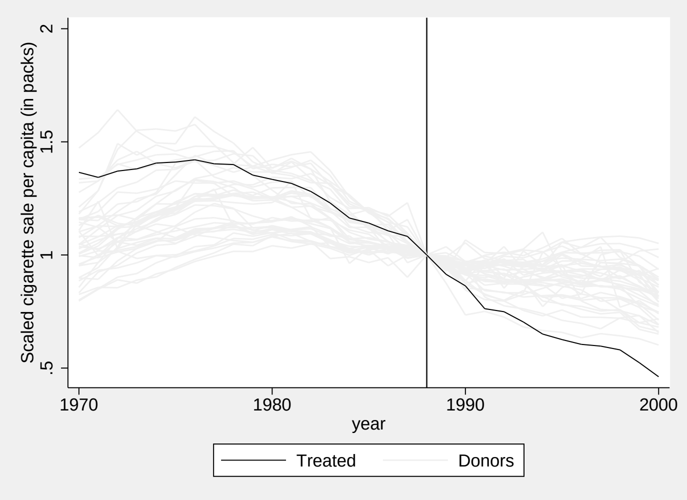
Diagnostics (want large values)

```
    e(avg_pre_rmspe_p) = .631578947368421
    e(avg_val_rmspe_p) = .8421052631578947
```

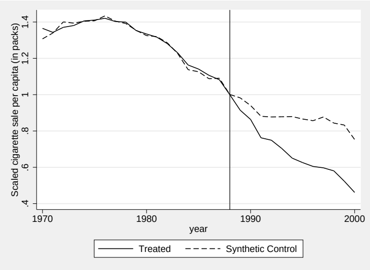
Make Graphs

```
merge 1:1 state year using `keepfile2', nogenerate
gen cigsale_scaled_synth = cigsale_scaled - effect_scaled
single_treatment_graphs, depvar(cigsale_scaled) effect_var
    (effect_scaled) trunit(3) trperiod(1989)
effect_graphs , depvar(cigsale_scaled) depvar_synth(
    cigsale_scaled_synth) effect_var(effect_scaled) trunit
     (3) trperiod(1989)
pval_graphs
```

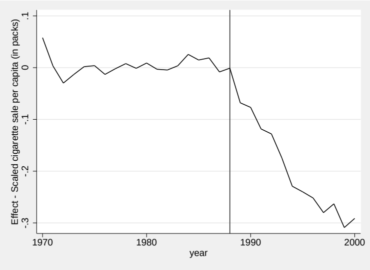
Outcome Trends



Mean Treated and Synthetic Control

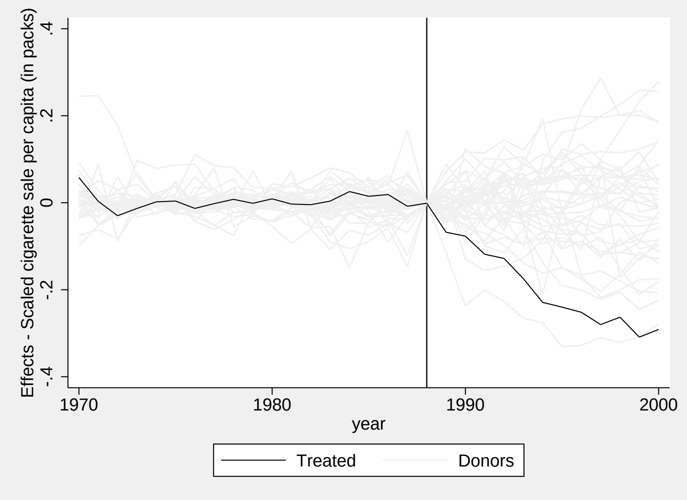


(e) Treated and Control

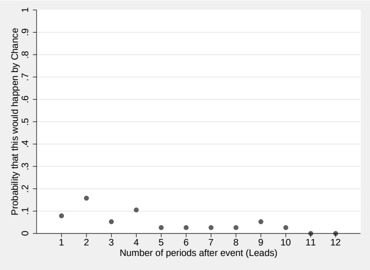


(f) Difference

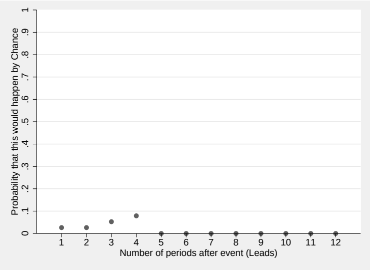
Differences



P-Values



(g) Effect



(h) Studentized Effect

Multiple Treatments

Placebo Set

- The number of SC estimates grows linearly ($J \cdot G$) while the size of the placebo set grows exponentially (J^G)
- Inference can quickly become infeasible
- By default, there is a maximum number (max) of averages computed for inference (1,000,000)
    - If $J^G < max$ then all J^G are used for inference
    - If $J^G > max$ then max are drawn at random (with replacement)
    - (max is modifyable and can be set to ∞)
- Space requirements scale exponentially if confidence intervals as desired, otherwise scales linearly.

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Estimate with Multiple Treatments

```
gen byte D = (state==3 & year>=1989) | (state==7 & year
    >=1988)
synth_runner cigsale beer(1984(1)1987) lnincome(1972(1)
    1987) retprice age15to24, d(D) trends training_propr
    (`=13/18')
*Graphs
effect_graphs , multi depvar(cigsale)
pval_graphs
```

Returned Values

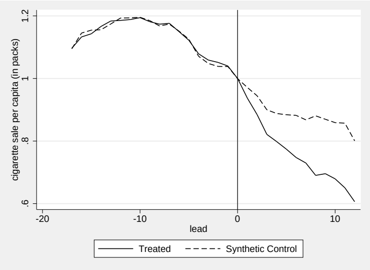
Post-treatment joint significance

```
    e(pval_joint_post) = .0423666910153397
e(pval_joint_post_std) = 0
```

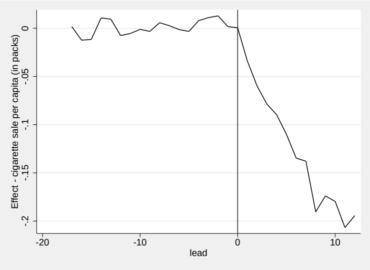
Diagnostics (want large values)

```
    e(avg_pre_rmspe_p) = .9298758217677137
    e(avg_val_rmspe_p) = .9598246895544192
```

Mean Treated and Synthetic Control

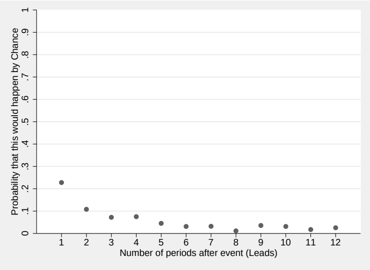


(i) Mean Treated and Control

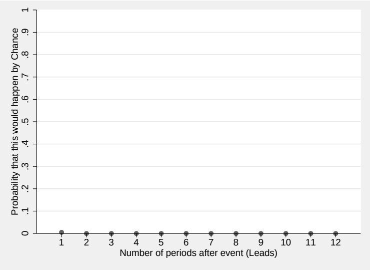


(j) Mean Difference

P-Values



(k) Effect



(l) Studentized Effect

Installation

- Stable Version:
  http://econweb.umd.edu/~galiani/code.html
- Development:
  https://github.com/bquistorff/synth_runner
  - Can submit bug reports and patches.

Future Work for synth_runner

- Cross-validation for picking regressors (Dube and Zipperer, 2015).
- Graph the ratio of post/pre RMSPE (as in ?)
- Leave-one-observation-out robustness:
  - Small number: Graph as in ?. Would also want to show changing significance levels.
  - Large number: Standard deviation of the change of the estimate $\{(\hat{\alpha} - \hat{\alpha}_{-j}\}_j$ (Athey and Imbens, 2015). What proportion lose/gain significance?
- Allow per-treatment donor sets e.g. to limit interpolation bias (non-linear DGP) or spill-overs.
- CV for picking V (mentioned in Abadie et al. 2010 and used in ?) using training period

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Q & A

Appendix Slides

Alberto Abadie and Javier Gardeazabal. The economic costs of conflict: A case study of the Basque country. *American Economic Review*, 93(1):113–132, March 2003. doi:10.1257/000282803321455188.

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