DOCUMENTS DE TRAVAIL CEMOI / CEMOI WORKING PAPERS

A SAS macro for estimation and inference in differences-in-differences applications with within cluster correlation and cluster-corrections for a few clusters

Nicolas Moreau[1]

http://cemoi.univ-reunion.fr

Centre d'Economie et de Management de l'Océan Indien
Université de La Réunion

June 2017

Abstract

This paper presents a SAS macro written for estimation and inference in differences-in-differences applications with clustering. Cluster robust variance estimators for within-group error correlation are implemented. Finite cluster-corrections for a few clusters are also performed.

JEL: C210, C810

[1] E-mail: nicolas.moreau@univ-reunion.fr

Introduction

Here we introduce the SAS macro *DiD_CLUS* written for estimation and inference in differences-in-differences applications with within cluster correlation. Cluster robust variance estimators for within-cluster error correlation are implemented. Cluster-correction to improve finite-sample inference when the number of clusters is small is also incorporated; it includes Bell and McCaffrey's (2002) bias-corrected variance, Wild bootstrap and use of the T distribution with Bell and McCaffrey's (2002) and Imbens and Kolesár's (2016) adjusted degrees-of-freedom.[2]

The SAS macro *DiD_CLUS* considers both group×time and individual-level data. It mixes SAS procedures and lines of code written with SAS/IML. The complete code is available at http://cemoi.univ-reunion.fr/econometrie-avec-r-et-sas/.

Differences-in-differences estimates with the SAS macro *DiD_CLUS*

For group×time level data, the model is:

$$y_{gt} = \alpha d_{gt} + W_{gt}\delta + \theta_g + \gamma_t + e_{gt}, \quad (1)$$

where d_{gt} is the policy variable, W_{gt} a vector of regressors, θ_g a time-invariant fixed effect for group g, γ_t a fixed time effect that is common across all groups but varies across time $t = 1, \dots, T$, and e_{gt} a group-by-time error term. The subscript g is used to index the group, the subscript t to index the time period.

For individual-level data, the model specification is:

$$y_{igt} = \alpha d_{gt} + W_{gt}\delta + Z_i\varphi + \theta_g + \gamma_t + e_{igt},$$

where Z_i is a vector of individual-specific regressors. Note that because the policy variable d_{gt} is only observed at the group×time level, it is common first to aggregate the individual-level data to the group×time level, then to OLS regress the model:

$$\tilde{y}_{gt} = \alpha d_{gt} + W_{gt}\delta + \theta_g + \gamma_t + e_{gt}, \quad (2)$$

where $\tilde{y}_{gt}$ is the average of the outcome variable y in group g and time period t after partialling out individual-specific covariates. To compute $\tilde{y}_{gt}$, *DiD_CLUS* uses a two-step approach advocated by Hansen (2007), Conley and Taber (2011), and Cameron and Miller (2015). First, *DiD_CLUS* runs the OLS regression of the dependent variable y_{igt} on all group-by-time dummies and individual-specific covariates Z_i, with no constant. Second, $\tilde{y}_{gt}$ equals the estimated coefficients of the group-by-time dummies. If the model does not include any individual-specific covariates, $\tilde{y}_{gt}$ is only the average of y_{igt} within the group-time cell.

To estimate the treatment effect α and the vector of parameters δ, *DiD_CLUS* additionally partials out the group and time dummies by applying the Frisch-Waugh-Lovell theorem. *DiD_CLUS* regresses y_{gt} (or $\tilde{y}_{gt}$ if equation (2) is used), d_{gt}, and X_{gt} on the group and year dummies, with no constant. Then α and δ are estimated by regressing the residuals of y_{gt} (or $\tilde{y}_{gt}$ if equation (2) is used) on the residuals of d_{gt} and X_{gt}, with no constant.

Inference with the SAS macro *DiD_CLUS*

Let y_{gt} denote the outcome variable in equations (1) and (2), and X_{gt} a vector that consists of all covariates and fixed effects in equations (1) and (2). Stacking all observations in the g^{th} cluster, equations (1) and (2) can be rewritten as:

$$y_g = X_g\beta + e_g, \quad g = 1, \dots, G, \qquad (3)$$

where y_g and u_g are $N_g \times 1$ vectors, X_g is a matrix with N_g rows, and there are N_g observations in cluster g. The OLS estimator is:

$$\hat{\beta} = \left(\sum_{g=1}^{G} X_g^T X_g\right)^{-1} \sum_{g=1}^{G} X_g^T y_g.$$

Given error dependence across clusters, the cluster covariance matrix estimator conditional on X is:

$$Var_{CLU}(\hat{\beta}|X) = \left(\sum_{g=1}^{G} X_g^T X_g\right)^{-1} \left(\sum_{g=1}^{G} X_g^T E[e_g e_g^T|X] X_g\right)\left(\sum_{g=1}^{G} X_g^T X_g\right)^{-1}.$$

[2]One of the problems for statistical inference with few clusters is over-rejection of the null hypothesis. We refer the reader to Cameron and Miller (2015) for a clear and comprehensive presentation of existing corrections.

The SAS macro *DiD_CLUS* computes the cluster-consistent covariance matrix estimator:

$$\widehat{Var}_{CLU}(\hat{\beta}) = \left(\sum_{g=1}^{G} X_g^T X_g\right)^{-1} \left(\sum_{g=1}^{G} X_g^T \hat{e}_g \hat{e}_g^T X_g\right)\left(\sum_{g=1}^{G} X_g^T X_g\right)^{-1}, (4)$$

where $\hat{e}_g = y_g - X_g\hat{\beta}$ is the vector of residuals for the g^{th} cluster.

To reduce downwards bias in (4) due to finite *G*, the SAS macro *DID_CLUS* also provides two finite-sample modifications of $\widehat{Var}_{CLU}(\hat{\beta})$ described in Cameron and Miller (2015).

$\widehat{Var}_{CLU,adj1}(\hat{\beta})$ uses $\sqrt{c}\hat{e}_g$ in (4) instead of $\hat{e}_g$, with

$$c = \frac{G}{G-1}\frac{N-1}{N-np},$$

where *N* is the number of observations and *np* the number of parameters to estimate.

$\widehat{Var}_{CLU,adj2}(\hat{\beta})$ uses:

$$c = \frac{G}{G-1}.$$

When the number of clusters is small, test-statistics based on $\widehat{Var}_{CLU}(\hat{\beta}), \widehat{Var}_{CLU,adj1}(\hat{\beta})$ and $\widehat{Var}_{CLU,adj2}(\hat{\beta})$ tend to over-reject the null.

The SAS macro *DiD_CLUS* incorporates some of the finite-sample corrections that are presented in Cameron and Miller (2015) to circumvent this problem.

Bias-corrected cluster robust covariance matrix

The bias-reduction modification developed by Bell and McCaffrey (2002) uses $\left[I_{N_g} - P_{gg}\right]^{-1/2} \hat{e}_g$ in (4) rather than $\hat{e}_g$, where P_{gg} is the $N \times N_g$ matrix $X_g(X^TX)^{-1}X_g^T$, and $\left[I_{N_g} - P_{gg}\right]^{-1/2}$ the inverse of the symmetric square root of $I_{N_g} - P_{gg}$. Therefore, the bias corrected cluster robust covariance matrix implemented in the SAS macro *DiD_CLUS* is:

$$\widehat{Var}_{CLU2}(\hat{\beta}) = \left(\sum_{g=1}^{G} X_g^T X_g\right)^{-1} \left(\sum_{g=1}^{G} X_g^T \left[I_{N_g} - P_{gg}\right]^{-1/2} \hat{e}_g \hat{e}_g^T \left[I_{N_g} - P_{gg}\right]^{-1/2} X_g\right)\left(\sum_{g=1}^{G} X_g^T X_g\right)^{-1}.$$

Degrees of freedom adjustment

The simplest adjustment implemented in the SAS macro *DiD_CLUS* is approximating the distribution of t-statistics by a T-distribution with *G-1* degrees of freedom. The SAS macro *DiD_CLUS* further includes Bell and McCaffrey's (2002) and Imbens and Kolesár's (2016) data-determined degrees of freedom. They are calculated only for t-statistics computed with $\widehat{Var}_{CLU2}(\hat{\beta})$.

Let $\boldsymbol{G}$ denote the $N \times G$ matrix with g[th] column equal to the *N*-vector:

$$\boldsymbol{G}_g = (I_N - P)_g (I_{N_g} - P_{gg})^{-1/2} X_g (X^TX)^{-1} u_k,$$

where P is the projection matrix $X(X^TX)^{-1}X^T$, $(I_N - P)_g$ the $N \times N_g$ matrix that consists of the N_g columns of $(I_N - P)$ corresponding to cluster g, and u_k a vector of zeros aside from 1 in the k^{th} position.

Bell and McCaffrey's (2002) degrees of freedom adjustment is given by:

$$dof_{BM} = \frac{(\sum_{i=1}^{N} \lambda_i)^2}{\sum_{i=1}^{N} \lambda_i^2},$$

where λ_i are the eigenvalues of $\boldsymbol{G}^T\boldsymbol{G}$.

Imbens and Kolesár's (2016) degrees of freedom adjustment is:

$$dof_{IK} = \frac{(\sum_{i=1}^{N} \tilde{\lambda}_i)^2}{\sum_{i=1}^{N} \tilde{\lambda}_i^2},$$

where $\tilde{\lambda}_i$ are the eigenvalues of $\boldsymbol{G}^T\widehat{\Omega}\boldsymbol{G}$, $\Omega = E[uu^T|X]$ assuming equicorrelated errors so that $\widehat{\Omega}_{ij} = \hat{\sigma}_e^2$ if $i = j$, $\widehat{\Omega}_{ij} = \hat{\rho}$ if $i \neq j$ and $G_i = G_j$, $\widehat{\Omega}_{ij} = 0$ otherwise.

Wild cluster bootstrap

In the SAS macro *DiD_CLUS*, the Wild bootstrap is used to test the null hypothesis of no treatment effect $\alpha = 0$. Let $\hat{\alpha}$ be the estimate of the treatment effect, and let $\hat{\sigma}_{\hat{\alpha}}$ be its estimated standard error calculated with $\widehat{Var}_{CLU}$. Let $t_{\hat{\alpha}} = \frac{\hat{\alpha}}{\hat{\sigma}_{\hat{\alpha}}}$ be the corresponding t-statistic. The approach is to calculate a p-value for $t_{\hat{\alpha}}$ from a distribution of B bootstrap t-statistics $t_{\hat{\alpha},b} = \frac{\hat{\alpha}_b}{\hat{\sigma}_{\hat{\alpha}_b}}, b = 1, \ldots B$. There are several ways to do so. The SAS macro *DiD_CLUS* implements the method presented in Cameron and Miller (2015).

First, estimate equation (3) under the null hypothesis of the no treatment effect $\alpha = 0$. Second, form the vector of residuals $\tilde{e}_g = y_g - X_g^T \tilde{\beta}_{\alpha=0}$. Third, the value of the outcome in the b^{th} bootstrap replication for cluster g is redrawn as:

$$y_{g,b} = X_g^T \tilde{\beta}_{\alpha=0} + w_{g,b}\tilde{e}_g, \qquad b = 1, \ldots, B$$

where the weight $w_{g,b}$ is randomly assigned. With Rademacher weights, $w_g = \{-1,1\}$ and $\Pr(w_{g,b} = 1) = \Pr(w_{g,b} = -1) = 0.5$. With Webb's (2014) weights, $w_g = \left\{-\sqrt{1.5}, -1, -\sqrt{0.5}, \sqrt{0.5}, 1, \sqrt{1.5}\right\}$ and $\Pr(w_{g,b} = -\sqrt{1.5}) = \Pr(w_{g,b} = -1) = \Pr(w_{g,b} = -\sqrt{0.5}) = \Pr(w_{g,b} = \sqrt{0.5}) = \Pr(w_{g,b} = 1) = \Pr(w_{g,b} = \sqrt{1.5}) = 1/6$.

Fourth, regress y_b on X to obtain $\hat{\beta}_b$. Extract $\hat{\alpha}_b$ from $\hat{\beta}_b$ and compute the bootstrap t-statistic $t_{\hat{\alpha},b} = \frac{\hat{\alpha}_b}{\hat{\sigma}_{\hat{\alpha}_b}}$.

Fifth, the p-value for the t-statistic $t_{\hat{\alpha}}$ calculated on the original sample is calculated by:

$$\hat{p}(t_{\hat{\alpha}}) = 2\min\left(\frac{1}{B}\sum_{b=1}^{B} I(t_{\hat{\alpha},b} \le t_{\hat{\alpha}}), \frac{1}{B}\sum_{b=1}^{B} I(t_{\hat{\alpha},b} > t_{\hat{\alpha}})\right),$$

where *I*(.) is the standard indicator function (see Webb, 2014).

Webb (2014) shows that there are actually only 2^{G-1} possible t-statistics in absolute value with Rademacher weights. It is a problem when *G* is small because unique values of $t_{\hat{\alpha},b}$ will be found multiple times in the vector of bootstrap t-statistics. The *B* t-statistics cannot be treated as *B* unique values. As a consequence, the p-value $\hat{p}(t_{\hat{\alpha}})$ is not point-identified but is instead an interval (Webb (2014), p. 6). If $t_{\hat{\alpha}} = t_{\hat{\alpha},b}$ multiple times, the SAS macro *DiD_CLUS* computes lower and upper bounds for $\hat{p}(t_{\hat{\alpha}})$. With Webb's (2014) weights, this problem is really less likely to happen.

Syntax of the SAS macro *DiD_CLUS*

The syntax is: %*DiD_CLUS*(data=,depvar=,regtreat=,reg=,regind=,obsid=,groupid=,timeid=,breps=);.

data specifies the input data set. *depvar* is the outcome variable. *regtreat* is the policy variable. *reg* specifies the list of regressors X_{gt}; this list can be empty. *regind* specifies the list of regressors Z_i; this list can be empty. *obsid* is the variable that identified the observation *i*; it can be empty. *groupid* specifies the variable that identifies the group for each observation; it cannot be empty. *timeid* is the variable that identifies the time period for each observation in the input data; it cannot be empty. All variables in *depvar*, *regtreat, reg*,and *regind* must be numeric.

The parameter *breps* specifies the number of replications *B* used to perform Wild bootstrap p-values. Wild bootstrap cannot be processed if *breps* is left empty.

Output results of the SAS macro *DiD_CLUS*

The first four tables show the number and percentage of observations per group and time period as the distribution of the policy variable per group and time period.

A fifth table includes preliminary estimates from a pooled OLS estimation with standard errors robust to heteroskedasticity. With group-time or individual-level panel data a two-way fixed-effects model is also estimated. Estimation results are shown in a sixth table.

The OLS differences-in-differences estimates then follow. The table named "Estimation results: estimates, t-statistics and p-values" exhibits the parameter estimates and their standard errors from various different covariance estimators. "Default" is the usual OLS standard error assuming homoskedasticity and non-correlated errors. "White robust" is the OLS standard error robust to heteroskedasticity of unknown form. "Cluster robust" standard errors are calculated from $\widehat{Var}_{CLU}(\hat{\beta})$, "Cluster robust adj1" from $\widehat{Var}_{CLU,adj1}(\hat{\beta})$, "Cluster robust adj2" from $\widehat{Var}_{CLU,adj2}(\hat{\beta})$ and "Bias-corr. cluster robust" from $\widehat{Var}_{CLU2}(\hat{\beta})$. "P-value: z-dist" and "P-value: t-dist" are the p-values calculated using the standard normal distribution and t-distribution with *G*-1 degrees of freedom, respectively. "P-value: BM dof" and "P-value:

IK dof " are the p-values calculating using t-distribution with Bell and McCaffrey's (2002) and Imbens and Kolesár 's (2016) data-determined degrees of freedom. These degrees of freedom adjustments are made only for t-statistics calculated from the bias-corrected cluster robust covariance estimator.

The table named "Estimation results: estimates and 95% confidence intervals" presents lower and upper bounds of 95% confidence intervals calculated using the standard normal distribution or t-distribution with G-1 or data-determined degrees of freedom.

The table named "Data-determined degrees of freedom" indicates for each covariate the number of degrees of freedom calculated with Bell and McCaffrey's (2002) and Imbens and Kolesár 's (2016) methodology.

The last table exhibits inference with Wild bootstrap for the treatment effect parameter α.

An example

We illustrate the use of *DiD_CLUS* with data taken from a study of the effect of merit scholarship on college attendance as reported by Conley and Taber (2011).

coll=1 if college attendance, 0 otherwise
merit= 1 if recipient of merit scholarship, 0 otherwise
male= 1 if male, 0 otherwise
black= 1 if Black , 0 otherwise
asian= 1 if Asian, 0 otherwise
state: state of residence
year: time period.

The instructions:

```
%DiD_CLUS(data=lib.regmraw,depvar=coll,regtreat=merit,reg=,regind=male black
          asian,obsid=,groupid=state,timeid=year,breps=999);
```

give the following results:

POOLED OLS ESTIMATION ON ORIGINAL DATA, WITHIN CLUSTER CORRELATION NOT ACCOUNTED FOR

The REG Procedure
Model: MODEL1
Dependent Variable: coll

Number of Observations Read	42161
Number of Observations Used	42161

NOTE: No intercept in model. R-Square is redefined.

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	66	8677.28767	131.47406	549.77	<.0001
Error	42095	10067	0.23914		
Uncorrected Total	42161	18744			

Root MSE	0.48902	R-Square	0.4629
Dependent Mean	0.44458	Adj R-Sq	0.4621
Coeff Var	109.99608		

Parameter Estimates

Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
merit	Policy variable	1	0.03375	0.01470	2.30	0.0217
male		1	-0.07885	0.00477	-16.53	<.0001
black		1	-0.15037	0.00756	-19.90	<.0001
asian		1	0.16895	0.01360	12.42	<.0001
group_d1		1	0.44189	0.02538	17.41	<.0001
group_d2		1	0.48890	0.02729	17.91	<.0001
group_d3		1	0.44509	0.02823	15.77	<.0001
group_d4		1	0.58175	0.01567	37.13	<.0001
group_d5		1	0.52340	0.02771	18.89	<.0001
group_d6		1	0.59926	0.02558	23.42	<.0001
group_d7		1	0.53305	0.01210	44.04	<.0001
group_d8		1	0.58294	0.01480	39.39	<.0001
group_d9		1	0.50672	0.01399	36.21	<.0001
group_d10		1	0.50077	0.01358	36.87	<.0001
group_d11		1	0.43962	0.02225	19.76	<.0001
group_d12		1	0.56045	0.01398	40.09	<.0001
group_d13		1	0.53030	0.01380	38.43	<.0001
group_d14		1	0.53053	0.02125	24.97	<.0001
group_d15		1	0.47447	0.02237	21.21	<.0001
group_d16		1	0.54112	0.02221	24.36	<.0001
group_d17		1	0.49042	0.02403	20.41	<.0001
group_d18		1	0.57161	0.02068	27.64	<.0001
group_d19		1	0.45182	0.01969	22.95	<.0001
group_d20		1	0.54049	0.02091	25.84	<.0001
group_d21		1	0.54301	0.02138	25.39	<.0001
group_d22		1	0.50654	0.02705	18.72	<.0001
group_d23		1	0.57859	0.02727	21.22	<.0001
group_d24		1	0.50390	0.02913	17.30	<.0001
group_d25		1	0.57431	0.02151	26.70	<.0001
group_d26		1	0.43525	0.02126	20.48	<.0001
group_d27		1	0.51389	0.01483	34.66	<.0001
group_d28		1	0.51174	0.02278	22.46	<.0001
group_d29		1	0.41597	0.02316	17.96	<.0001
group_d30		1	0.42825	0.01453	29.48	<.0001
group_d31		1	0.40703	0.02283	17.83	<.0001
group_d32		1	0.38851	0.02291	16.96	<.0001
group_d33		1	0.50051	0.02108	23.74	<.0001
group_d34		1	0.50588	0.02238	22.60	<.0001
group_d35		1	0.36365	0.02469	14.73	<.0001
group_d36		1	0.47254	0.02171	21.76	<.0001
group_d37		1	0.46977	0.02200	21.35	<.0001
group_d38		1	0.41682	0.01289	32.33	<.0001
group_d39		1	0.46144	0.02128	21.69	<.0001
group_d40		1	0.39404	0.02065	19.08	<.0001
group_d41		1	0.44630	0.02212	20.18	<.0001
group_d42		1	0.40811	0.02394	17.05	<.0001
group_d43		1	0.37935	0.02233	16.99	<.0001
group_d44		1	0.40770	0.02216	18.40	<.0001
group_d45		1	0.45571	0.01993	22.87	<.0001
group_d46		1	0.34546	0.02504	13.80	<.0001
group_d47		1	0.45079	0.02412	18.69	<.0001
group_d48		1	0.44806	0.02295	19.52	<.0001
group_d49		1	0.46756	0.01134	41.24	<.0001
group_d50		1	0.41204	0.02178	18.91	<.0001
group_d51		1	0.40842	0.02819	14.49	<.0001

time_d2	1	-0.00802	0.01064	-0.75	0.4512
time_d3	1	0.00907	0.01084	0.84	0.4024
time_d4	1	0.01108	0.01105	1.00	0.3160
time_d5	1	0.02070	0.01107	1.87	0.0615
time_d6	1	0.01632	0.01117	1.46	0.1440
time_d7	1	-0.00287	0.01135	-0.25	0.8005
time_d8	1	0.01903	0.01149	1.66	0.0976
time_d9	1	0.00967	0.01150	0.84	0.4007
time_d10	1	0.02467	0.01147	2.15	0.0315
time_d11	1	0.00253	0.01147	0.22	0.8255
time_d12	1	0.01233	0.01181	1.04	0.2964

HCC Approximation Method: HC1

PANEL DATA ESTIMATION NOT POSSIBLE
POOLED DATA ARE USED OR THE INDIVIDUAL IDENTIFICATION VARIABLE IS MISSING

AGGREGATED DATA: DESCRIPTIVE STATISTICS

Number of observations	612
Number of clusters	51
Number of time periods	12

ESTIMATION RESULTS: ESTIMATES, T-STATISTICS AND P-VALUES

	Estimate	Std. Err	T-stat	P-value: z-dist	P-value: t-dist
Parameter: MERIT	0.051209	.	.	.	.
Standard Errors:	.	.	.	.	.
Usual	.	0.0188256	2.7201776	0.0065247	.
White robust	.	0.0130024	3.9384332	0.000082	.
Cluster robust	.	0.0106101	4.8264485	1.3899E-6	0.0000135
Cluster robust adj1	.	0.0107157	4.7788962	1.7626E-6	0.0000159
Cluster robust adj2	.	0.0107157	4.7788962	1.7626E-6	0.0000159
Bias-corr. cluster robust	.	0.0109065	4.6952807	2.6624E-6	0.0000211

Note: p-values are calculated using the standard normal distribution and t-distribution with G-1 degrees of freedom, respectively.

	Estimate	Std. Err	T-stat	P-value: BM dof	P-value: IK dof
MERIT	0.051209	0.0109065	4.6952807	0.0008202	0.0008202

Notes: p-values are calculated using t-distribution with data-determined degrees of freedom. Standard errors from the bias-corrected cluster robust covariance estimator are used.

Data-determined degrees of freedom

	MERIT
Bell and McCaffrey degrees of freedom	10.122
Imbens and Kolesár degrees of freedom	10.122

ESTIMATION RESULTS: ESTIMATES AND 95% CONFIDENCE INTERVALS

Estimate	L.bound	U.bound	L.bound/dof=G-1	U.bound/dof=G-1

Parameter: MERIT	0.051209	.	.	.	.
Standard Errors:	.	.	.	.	.
Usual	.	0.0143115	0.0881065	.	.
White robust	.	0.0257248	0.0766932	.	.
Cluster robust	.	0.0304136	0.0720044	0.029898	0.07252
Cluster robust adj1	.	0.0302067	0.0722113	0.029686	0.072732
Cluster robust adj2	.	0.0302067	0.0722113	0.029686	0.072732
Bias-corr. cluster robust	.	0.0298327	0.0725853	0.0293027	0.0731153

Note: lower and upper bounds of confidence intervals are calculated using the standard normal distribution and t-distribution with G-1 degrees of freedom, respectively.

	Estimate	L.bound/BM dof	U.bound/BM dof	L.bound/IK dof	U.bound/IK dof
MERIT	0.051209	0.0269475	0.0754705	0.0269475	0.0754705

Notes: lower and upper bounds of confidence intervals are calculated using t-distribution with data-determined degrees of freedom. Standard errors from the bias-corrected cluster robust covariance estimator are used.

ESTIMATION RESULTS: INFERENCE FOR THE TREATMENT EFFECT WITH WILD BOOTSTRAP POINT-IDENTIFIED P-VALUES

	Policy variable: merit
Parameter estimate	0.051209
Cluster robust SE	0.0106101
T-statistic	4.8264485
Bootstrap p-value Rademacher 2 weights	0.002002
Bootstrap p-value Webb 6 weights	0.002002

References

Bell, Robert M., and Daniel F. McCaffrey. 2002. "Bias reduction in standard errors for linear regression with multi-stage samples. " Survey Methodology 28(2): 169-81.

Cameron, A. Colin, and Douglas L. Miller. 2015. "A Practitioner's Guide to Cluster-Robust Inference." *Journal of Human Resources* 50(2): 317-72.

Conley, Timothy G., and Christopher R. Taber. 2011. "Inference with 'Difference in Differences' with a Small Number of Policy Changes." *Review of Economics and Statistics* 93(1): 113-25.

Hansen Hansen, Christian. 2007. "Generalized Least Squares Inference in Panel and Multi-level Models with Serial Correlation and Fixed Effects." *Journal of Econometrics* 141(2): 597-620.

Imbens, Guido W., and Michal Kolesár. 2016. "Robust Standard Errors in Small Samples: Some Practical Advice." *Review of Economic and Statistics* 98(4): 701-12.

Webb, Matthew D. 2014. "Reworking Wild Bootstrap Based Inference for Clustered Errors." Queen's Economics Department Working Paper No. 1315.