Reproduction with DoubleML of '*Hit or Miss? The Effect of Assassinations on Institutions and War*' by Benjamin F. Jones and Benjamin A. Olken

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1 Introduction

The paper "Hit or Miss? The Effect of Assassinations on Institutions and War" by Benjamin F. Jones and Benjamin A. Olken is located at: https://www.aeaweb.org/articles?id=10.1257/mac.1.2.55.

The data and code for replication can be accessed at: https://www.openicpsr.org/openicpsr/project/114047/version/V1/view.

- The paper analyses the effect of assassination attemps on changes in countries' political institutions (e.g., transition to democracy) and change in war status (e.g., emergence of conflicts and intensity)
- The fundamendal identification assumption is that the success of an assassination attempt is exogeneous of all unobserved causal factors. To make the hypothesis believable, the authors control for the type of weapon used in the assassination attempt and the number of attempts in a given country-year; indeed, different weapons have different lethality rates and success of an assassination depends directly on the number of attempts. The authors exclude other observable quantities based on their identical predictive power for success and failure
- Two caveats are in order: the results obtained by the author are almost invariant to the inclusion or exclusion of the controls; the controls considered are quite low-dimensional. We thus expect to find similar results when using DoubleML methods
- The authors consider the following linear specification:

  $$y_i = \beta \cdot SUCCESS_i + \gamma X_i + \varepsilon_i,$$

  where y_i is the outcome of interest (institution change or war status change), X is a number of control variables (type of weapons, number of attempts), and $SUCCESS$ is a dummy variable taking value 1 if the attempt is successful and 0 otherwise. The key identification assumption for the average treatment effect of a successful assassination attempt on y is given by the standard exogeneity condition:

  $$\mathbb{E}\big[\varepsilon | X, SUCCESS\big] = 0,$$

in which case, we obtain

$$\beta = \mathbb{E}\big[y|X, SUCCESS = 1\big] - \mathbb{E}\big[y|X, SUCCESS = 0\big]$$

2 Data and backend

We first run some Stata code to clean and retrieve the data according to the authors' routine as outlined in their code. We then load the data in a Pandas data frame in Python to reproduce the authors' OLS regressions and compute the same parameter estimates under DoubleML specifications (P. Bach et al 2022). We use version Python3.8, StatsModels for OLS, DoubleML for double machine learning methods, and econml.dml for the causal forest method (S. Wager & S. Athey 2018).

3 Reproducing the OLS results in Jones and Olken

3.1 With clustered SEs

We first reproduce the results Table 5 using clustered standard errors at the "'cowcode"' level. We find exactly the same result as in the paper.

Table 0: OLS Assassinations and Institutional Change (clustered SEs)

	(1) Absolute change in POLITY2 dummy	(2) Directional change in POLITY2 dummy	(3) Percentage of "regular" leader transitions in next 20 years
Panel A: Average Effect			
Success	0.091* (0.047)	0.079 (0.051)	0.111* (0.058)
Observations	221	221	138
Panel B: Split by regime type in year before attempt			
Success × autocracy		0.131** (0.055)	0.191** (0.086)
Success × democracy		−0.011 (0.083)	0.034 (0.043)
Observations		221	133

Standard errors in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

3.2 Without clustered SEs

In what follows, we recompute all the regressions in Table 5 but do not cluster standard errors at the "'cowcode"' level. In particular, the estimates for β remain the same as in the paper but the standard errors naturally change. We do this because we will compute the parameter estimates and standard errors with DoubleML with and without clustering so that everything can be compared properly.

Table 1: OLS Assassinations and Institutional Change

	(1) Absolute change in POLITY2 dummy	(2) Directional change in POLITY2 dummy	(3) Percentage of "regular" leader transitions in next 20 years
Panel A: Average Effect			
Success	0.091**	0.079	0.111*
	(0.042)	(0.044)	(0.072)
Observations	221	221	138
Panel B: Split by regime type in year before attempt			
Success × autocracy		0.131**	0.191**
		(0.052)	(0.089)
Success × democracy		−0.011	0.034
		(0.069)	(0.102)
Observations		221	133

Standard errors in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4 Reproducing the results in Jones and Olken with DML

We now reproduce the results in Jones and Olken with the DoubleML package (Bach et al 2022). We consider a partially linear model of the form

$$y = \beta \cdot SUCCESS + g_0(X) + \xi, \quad \mathbb{E}\big[\xi | SUCCESS, X\big] = 0$$

$$SUCCESS = m_0(X) + V, \quad \mathbb{E}\big[V|X\big] = 0$$

We use Random Forest Classifier for the first stage with $n = 200$ and max depth 5 and Random Forest Regressor with 200 estimators and max depth 5. For the DML procedure, we use a fivefold cross-fitting.

4.1 Without clustered SEs

For the obtained ATE estimations we used the median method, following Chernozhukov et al. Namely, we report:

$$\tilde{\theta}_0^{median} = median\{\tilde{\theta}_0^s\}_{s=1}^S$$

$$\hat{\sigma}^{2,median} = median\{\hat{\sigma}_s^2 + (\hat{\theta}_s - \tilde{\theta}^{median})(\hat{\theta}_s - \tilde{\theta}^{median})'\}_{s=1}^S,$$

where $median(\cdot)$ is a median operator. We use 100 repetitions for the estimation procedure to build the median estimators. Results are represented in Table 2 below:

Table 2: DML Assassinations and Institutional Change

	(1) Absolute change in POLITY2 dummy	(2) Directional change in POLITY2 dummy	(3) Percentage of "regular" leader transitions in next 20 years
Panel A: Average Effect			
Success	0.088^{*}	0.079	0.112^{**}
	(0.051)	(0.053)	(0.058)
Observations	221	221	138
Panel B: Split by regime type in year before attempt			
Success × autocracy		0.129^{**}	0.166^{*}
		(0.066)	(0.087)
Success × democracy		0.010	0.063
		(0.078)	(0.055)
Observations		221	133

Standard errors in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

We observe that the results (parameter estimates and standard errors) obtained with DoubleML in a PLR model are quite similar to the one obtained with a simple OLS regression in a linear model. As already mentioned, this was expected given that: 1. the controls are low-dimensional; 2. the OLS results are almost invariant by the inclusion or exclusion of them; 3. the ML methods should work with constant and linear functions (as supposed from 2.).

4.2 With clustered SEs

Here we rely on the result obtained by Chiang et al. (2021) implemented in DoubleML package to cluster standard errors on "cowcode" level, as it was done by Jones & Olken. The original paper proposes the following estimator:

$$\hat{\sigma}^2 = \hat{J}^{-1}\hat{\Gamma}\hat{J}^{-1}, \quad \text{where}$$

$$\hat{\Gamma} = \frac{1}{K^2}\sum_{(k,l)\in|K|^2}\Bigg[\frac{\min\{|I_k|,|J_l|\}}{(|I_k||J_l|)^2}\Bigg(\sum_{i\in I_k}\sum_{j\in J_l}\sum_{j'\in J_l}\psi(W_{ij},\bar{\theta},\hat{\eta}_{k,l})\psi(W_{i,j'},\bar{\theta}_0,\hat{\eta}_{k,l})+$$

$$+\sum_{i\in I_k}\sum_{i'\in J_l}\sum_{j\in J_l}\psi(W_{ij},\bar{\theta},\hat{\eta}_{k,l})\psi(W_{i',j},\bar{\theta}_0,\hat{\eta}_{k,l})\Bigg)\Bigg] \quad \text{and}$$

$$\hat{J} = \frac{1}{K^2}\sum_{(k,l)\in|K|^2}\frac{1}{|I_k||J_l|}\sum_{i\in I_k}\sum_{j\in J_l}\psi_a(W_{ij},\hat{\theta}_0,\hat{\eta}_{kl})$$

For the estimators, we again use the median method with 100 repetitions. The obtained results are represented in Table 3 below:

Table 3: DML Assassinations and Institutional Change with clustered errors

	(1) Absolute change in POLITY2 dummy	(2) Directional change in POLITY2 dummy	(3) Percentage of "regular" leader transitions in next 20 years
Panel A: Average Effect			
Success	0.085^{*}	0.077	0.111^{**}
	(0.047)	(0.051)	(0.056)
Observations	221	221	138
Panel B: Split by regime type in year before attempt			
Success × autocracy		0.127^{**}	0.162^{*}
		(0.059)	(0.087)
Success × democracy		0.014	0.067
		(0.079)	(0.044)
Observations		221	133

Standard errors in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

As we see, the results with clustered standard errors are similar to the one represented in Table 1 and also similar in terms of significance and magnitude to the original results obtained with OLS. We can also notice a slight decrease in standard errors compared to the DML results without clustering.

5 Robustness Check

5.1 Interactive regression model

For the first round of robustness check we use the interactive regression model (IRM):

$$y = g_0(SUCCESS, X) + U, \quad \mathbb{E}\big[U|SUCCESS, X\big] = 0$$

$$D = m_0(X) + V, \quad \mathbb{E}\big[V|X\big] = 0$$

and estimate

$$\theta_0 = \mathbb{E}\big[g_0(SUCCESS = 1, X) - g_0(SUCCESS = 0, X)\big].$$

We noticed, that a regular random forest without tuning predicts zero outcomes for $SUCCESS$ variable. It is consistent with the author's result when they use a number of variables to distinguish a successful attempt from a failure. It also happens due to the unbalances of the data. Using upweigting and tuning parameters in the gradient boosting method we were able to raise ACU ROC (which seems to be a more reliable measure than accuracy for unbalanced data) from the default 0.58 to 0.74. We used a 0.01255 learning rate, 3 leaves, 80 estimators and a weight equal to 3.32 for the underrepresented class. Then we run the DML procedure with the IRM model, using the aforementioned LGBM classifier for the first stage and clustering standard errors as we did in the previous section. Again, we used the median method and 100 repetitions. The results are represented below:

Table 4: DML IRM Assassinations and Institutional Change with clustered errors

	(1) Absolute change in POLITY2 dummy	(2) Directional change in POLITY2 dummy	(3) Percentage of "regular" leader transitions in next 20 years
Panel A: Average Effect			
Success	0.073**	0.070*	0.125*
	(0.033)	(0.037)	(0.074)
Observations	221	221	138
Panel B: Split by regime type in year before attempt			
Success × autocracy		0.155***	0.174***
		(0.028)	(0.046)
Success × democracy		−0.102	0.054
		(0.031)	(0.061)
Observations		221	133

Standard errors in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

As we know from the theory, the DML procedure gives an asymptotically unbiased estimator. However, since we have very few observations, the performance in the first stage may play an important role in the final result. Furthermore, following the original paper, we know, that covariates do not help to predict the *success* variable in a linear function specification. This observation with our obtained result for the LGBM model justifies the reason for using IRM. As we see, obtained standard errors are reasonably lower, than in Tables 2 and 3, giving a higher significance to the coefficients of interest. The magnitudes of the coefficients are consistent with the original paper and previous results.

5.2 Causal forest

Next, we use the causal forest approach from econml.dml. We learn the forest on the train sample that represents 75% of the data and then estimates the ATE on the test sample of covariates, representing 25% of the data. Following Chernozhukov et al (2018), since we have rather few observations, we estimate casual forest with fivefold and twofold cross-fitting. For our purposes, we use the "het" criterion, which finds splits that maximize the pure parameter heterogeneity score. We use 100 estimators with a maximum length equal to 5 and honest trees. For the coefficients and standard errors, we again use the median approach with 100 repetitions. The results obtained are represented below:

Table 5: Causal Forest Assassinations and Institutional Change

	(1) Absolute change in POLITY2 dummy	(2) Directional change in POLITY2 dummy	(3) Percentage of "regular" leader transitions in next 20 years
Panel A: Average Effect			
Success (5 folds)	0.103*	0.077	0.111*
	(0.065)	(0.057)	(0.059)
Success (2 folds)	0.116*	0.087	0.130*
	(0.066)	(0.072)	(0.070)
Observations	221	221	138
Panel B: Split by regime type in year before attempt			
Success × autocracy (5 folds)		0.157**	0.167***
		(0.072)	(0.061)
Success × democracy (5 folds)		−0.057	0.074
		(0.065)	(0.093)
Success × autocracy (2 folds)		0.109***	0.142***
		(0.022)	(0.014)
Success × democracy (2 folds)		−0.121	0.033
		(0.021)	(0.032)
Observations		221	133

Standard errors in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

As we see, the results are consistent with all the previous estimates. We can notice, that for Panel A the obtained standard errors with twofold estimation are actually higher, than with fivefold estimation. However, it is the opposite for Panel B. Overall, we see that the fivefold estimation for Panel B gives similar to the IRM model with a tuned LGBM classifier results in terms of the magnitude and significance level. At the same time, twofold results are tangibly lower in magnitude and closer to the DML results with clustered errors.

6 Conclusion

We successfully reproduced the results in Jones and Olken: we first exactly reproduced the original results using the same data and the same linear specifications estimated by OLS ; we then used DoubleML methods and considered a more robust semiparametric specification which resulted in sensibly similar results from the paper. We then realized a number of robustness checks that confirmed the validity of the original results. The results we obtained were expected from the start: even in the original paper, the controls included by the authors did not play a significant role; the switch to a robust approach that better takes them into account was likely to deliver similar results.

References

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