E797B - Replication and Extension of DDCG by Acemoglu, Naidu, Restrepo and Robinson (2019)

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Part 1

Columns 1 to 3 of Table 2 in the original paper present the results of the baseline estimate effect of democracy on growth, which is obtained by the following dynamic panel model:

$$y_{ct} = \beta Dem_{ct} + \sum_{j=1}^{p} \gamma_j y_{ct-j} + \alpha_c + \delta_t + \epsilon_{ct}$$

Dem is the measure for democracy and the estimations include country and year fixed effects as well as p lags in GDP per Capita. The first two control for unobserved individual time-invariant and time-variant heterogeneity, respectively. The introduction of GDP lags arises from the empirical fact that democratizations are generally preceded by, on average, 5 to 4 year of decreases in GDP. A failure to account for this dynamics will produce biased estimates. I present the results of the estimation using robust and clustered standard error at the country level in Table 1.

The results match the originals, showing a positive and significant coefficient of democracy. Additionally, the authors calculate the persistence and the long run effect of democracy. The former is obtained by adding the coefficients of the GDP lags $\sum_{j=1}^{p} \hat{\gamma}$ and the latter by applying the formula $\frac{1}{1-\sum_{j=1}^{p} \hat{\gamma}_j}$. The reported standard errors are the ones associated to testing the null hypothesis that these two expressions are equal to zero. The authors also conduct a stationarity test on GDP. In particular, they test the null hypothesis that GDP has a unit root using Levin et.al procedure. Both the t-statistic and the associated p-value are reported in the bottom rows of Table 1, rejecting the existence of a unit root and hence showing evidence in favour of GDP being stationary.

In the remaining of this exercise, I will estimate the effect of democratization on GDP for different years. if a country transitioned to democracy in time t, then the authors define $\Delta y_{ct}^{s} = y^{s} - y_{t-1}$, which represent the percentage change in GDP s years after democratization. These will be the dependent variables in what remains of the exercise. The relevant independent variable is D_{ct}, which is equal to 1 if $Dem_t = 1$ and 0 if $Dem_{t-1} = 0$. Intuitively, β^s represents the effect of democratization on GDP growth s years after democratization. However, for β^s to be unbiased, countries that democratized and those who did not must have the same potential outcomes, which in general is not true. The treatment effects and semiparametric estimates that the authors implement solve this problem by modeling the the propensity to democratize as a function of observable variables. The assumption is that, once accounting for those factors, the selection into democracy is as good as random and hence βs is unbiased. The authors follow three approaches: Linear Regression Adjustment, Inverse-Propensity-Score-Reweighting and a Doubly Robust Estimator. In all cases, the propensity to democratize is modeled as a function of four GDP lags (for the reasons explained) above and year-fixed effects. I estimated the effect using teffects ra, ipw and ipwra, respectively, for each dependent variable Δy^s, $s = -15, ..., 30$. The results are shown in Table 2, which is a replication of Table 5 in the original paper.

Table 1: Effect of Democracy on (Log) GDP per Capita

	Within Estimates		
	(1)	(2)	(3)
Democracy	0.973	0.651	0.787
	(0.294)	(0.248)	(0.226)
Log GDP,	0.973	1.266	1.238
first lag	(0.006)	(0.038)	(0.038)
Log GDP,		-0.300	-0.207
second lag		(0.037)	(0.046)
Log GDP,			-0.026
third lag			(0.028)
Log GDP,			-0.043
fourth lag			(0.017)
Long-run	35.587	19.599	21.240
effect of democracy	(13.998)	(8.595)	(7.215)
Persistence	0.973	0.967	0.963
	(0.006)	(0.005)	(0.005)
Effect of	17.791	13.800	16.895
democracy: 25 years	(5.649)	(5.550)	(5.297)
Unit root test			
t- statistics	-4.79	-3.89	-4.13
p value (reject			
unit root	0.00	0.00	0.00
Observations	6790	6642	6336
Countries in			
sample	175	175	175

The numbers in each cell are the 5 years average of the estimates and the standard errors associated to the test of the null hypothesis that the average effect of democratization during those five years is equal to zero. The standard errors are clustered at the country level and estimated by bootstrap. The estimated coefficients match the ones obtained by the authors, although the standard errors are slightly different. The reason may be that they do 100 bootstrap repetitions (see footnote 19) whereas I did 20 due to computational constraints. In any case, the results and significance are the same. Moreover, in all subsequent estimations, I will get very similar results to what I present in Table 2 and show graphically in figures 3 and 4. Those results are that:

- $\hat{\beta}^s$ is not statistically different of zero for all $s < 0$ (just what we would expect if we control for the GDP lags)
- $\hat{\beta}^s$ is increasing in time after democratization but is not statistically significant for $s < 10$
- $\hat{\beta}^s$ becomes statistically significant and reaches its global maximum when $s \in [15, 24]$
- $\hat{\beta}^s$ starts declining and is no longer statistically significant for the very last values of s

These results are robust for the three different specifications presented in Table 5.

Table 2: Semiparametric estimates of the effect of democratizations on (log) GDP per Capita

	Average Effects From						
	-5 to -1 Years (1)	0-4 Years (2)	5-9 Years (3)	10-14 Years (4)	15-19 Years (5)	20-24 Years (6)	25-29 Years (7)
	A. Linear Regression Adjustment						
Avg. effect on log GDP	0.060	2.454	3.621	7.806	14.037	24.075	21.310
	(0.158)	(1.749)	(3.183)	(4.780)	(5.805)	(8.090)	(8.607)
	B. Inverse-Propensity-Score-Reweighting						
Avg. effect on log GDP	-1.586	3.724	3.214	6.818	13.542	24.111	22.184
	(1.386)	(2.563)	(3.242)	(5.045)	(5.805)	(7.934)	(9.009)
	C. Doubly Robust Estimator						
Avg. effect on log GDP	0.051	2.795	2.969	6.966	12.947	23.691	21.793
	(0.166)	(1.968)	(3.320)	(5.032)	(5.939)	(7.409)	(8.934)

Part 2

In this part, I estimate the following equation:

$$\Delta y_c^s = \beta^s D_{ct} + \sum_{j=1}^{p} \gamma_j y_{ct-j} + \epsilon_c$$

For $s = -15, ..., 30$, $p = 0$ (no lags) and $p = 4$. When $p = 0$, β^s is the simple double differences estimator; that is:

$$\beta^s = [\bar{y}_{D=1,post(s)} - \bar{y}_{D=1,pre}] - [\bar{y}_{D=0,post(s)} - \bar{y}_{D=0,pre}]$$

I present my results graphically in figure 1. In contrast to what was specified in Part 1, the figure shows a positive and significant effect of democratization on GDP growth before the event takes place; a negative effect (although not statistically significant) for the first 10 years after democratization, and a positive effect afterwards but only statistically significant around 15 and 20 years after democratization.

These differences can be fully explained by the absence of control for the dip that takes place before democratization. In fact, if we assume that, on averages, countries that did not democratized have non-negative GDP growth before the event, we would have: $\bar{y}_{D=1,post(s)} > \bar{y}_{D=1,pre}$ and $\bar{y}_{D=0,post(s)} \leq \bar{y}_{D=0,pre}$ for $s < 0$, which implies $\beta^s > 0$.

However, when I include the 4 GDP lags, non of these anomalies remain. I present the results in Figure 2. The estimated coefficient for $s \in [0, 4]$ is zero because the dependent variable is present as a covariate. Besides that, we observe the same patterns that were described in part 1. This illustrates the importance of always controlling for the factors that affect the propensity to get treated.

Figure 1: Diff-in-Diff Estimates

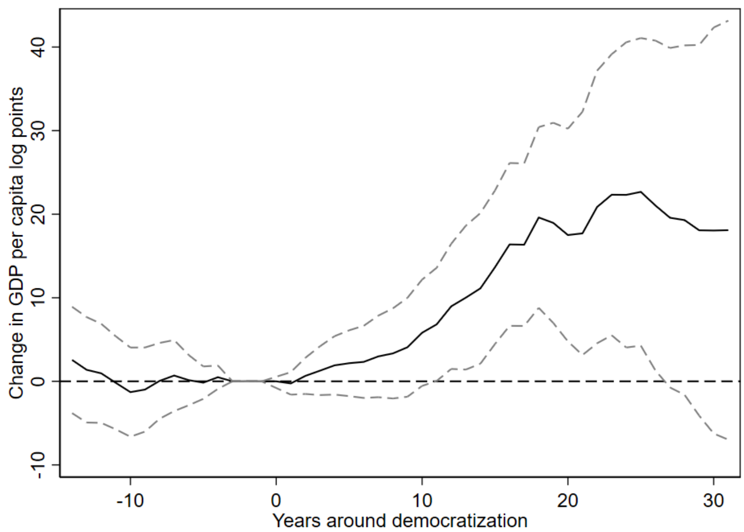

Figure 2: Diff-in-Diff Estimates controlling for 4 GDP lags

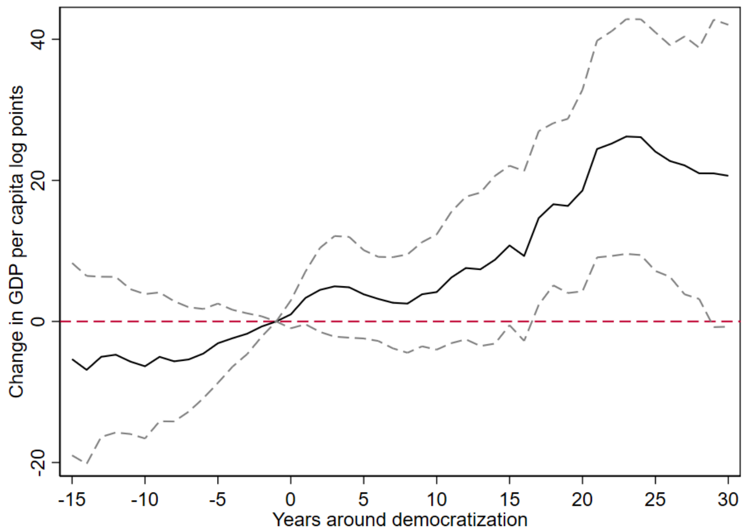

Figure 3: Propensity-Score-Reweighting estimates

Part 3

In this part I present a graphical a representation of rows 2 and 3 of (my) Table 1. They show $\hat{\beta}^s$ and the 95% confidence interval for the inverse PSR (figure 3) and doubly robust estimators (figure 4). In those figures we can see the results that were explained in part 1. Additionaly, we can compare them with the correct diff-in-diff estimates that we showed in figure 2. The 3 figures have basically the same shape, although the PSR and DR estimates give a greater maximum and in general the graph is steeper.

The other difference has to do with standard errors. For diff-in-diff, the confidence interval is in general wider and becomes even more for the last 5 years in the estimation. In contrast, for PSR and DR the estimate only becomes insignificantly different from zero for the last year.

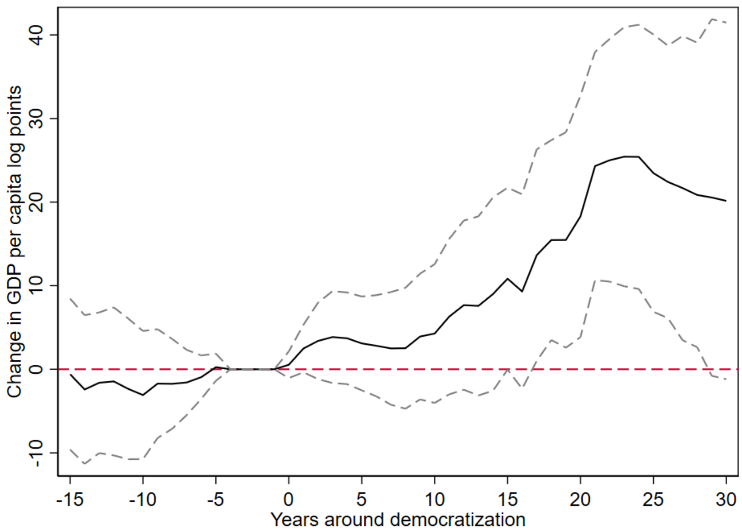

Figure 4: Doubly Robust estimator

Part 4

Now, instead of analyzing the effect of democratization on growth by considering many treated units and many treated controls, I conduct the analysis of each separate event. Country k is "treated" and there is an event associated if it transitioned to democracy without reversal. Country j is a clean control of country k if $dem = 0 \ \forall \ t < t_d + 20$, where t_d is the year in which country k transitioned to democracy.

I define the variable $Event\_k$, which is equal to 1 for country k at $t = t_d$ and zero for all clean controls j. It is a missing value for countries that were democracies at any moment before $t_d + 21$. I do this for all K countries that transitioned to democracy without reversal, and hence analyze separately those K events.

4 (a)

In this part I estimate the equation:

$$\Delta y^s_{c(k)} = \beta^s_k Event\_k + \sum_{j=1}^{4} \gamma_j y_{t-j} + \epsilon_{c(k)}$$

For each event k. This estimation is equivalent to the diff-in-diff with four lags that I did in part 2, but considering only the treated unit. I obtain $\hat{\beta}^s_k$ for $s = 15, .., 19$ and then I calculate $\bar{\beta}_k = \frac{1}{5}\sum_{s=15}^{19} \beta^s_k$ for all events k. The distribution of $\bar{\beta}$ is shown in figure 5 and the descriptive statistics in Table 3.

Compareing these results with those obtained in Table 5, we can see that the average effect is 18.11, whereas the average effect obatined with the semi-parametric approach

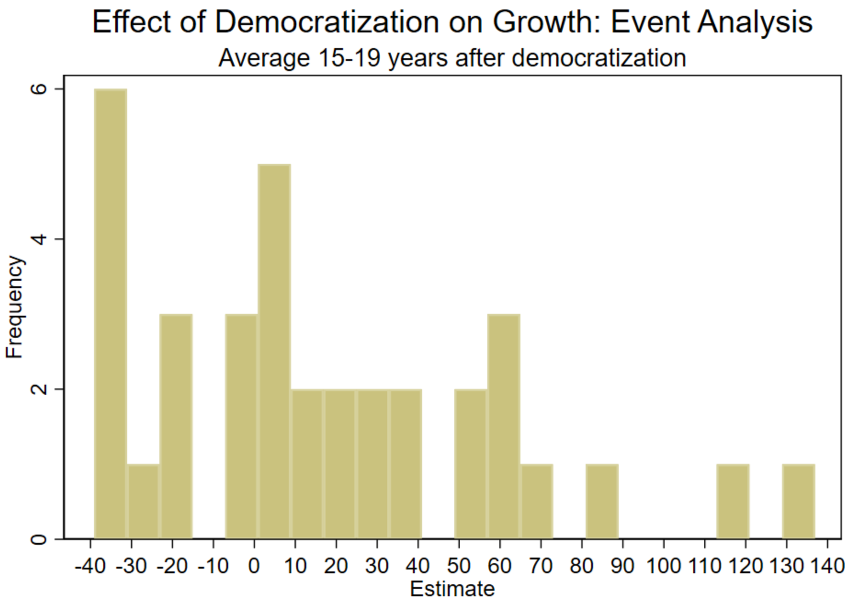

Figure 5: Distribution of event Diff-in-Diff estimates

Table 3: Summary of Event-Estimates

	Obs.	Mean	Median	Std. Dev.
Average Effect 15-19 years	35	18.11	6.9	43.11

goes from 12.95 to 14.04. The difference may not only be due to the different estimators being used, but also to the fact that in this part we are only considering democratizations without reversals, whereas in part 1 all democratizations enter into the treatment variable (in this case there are only 35 events, once we do not consider democratizations that happened less than 19 years before 2010, the last year we have data). However, the most salient fact is the big heterogeneity in the treatment effect. This can be seen in three different facts: first, we have a standard deviation of 43.03 log points. Secondly, there is a 10 log points difference between the median and the average effect. Finally, in the histogram we can see how there are 6 events with an average 15-19 years effect between -30 and -40 log points, and two events with an averages between 110 and 140 log points. Although most of the effects are positive, those outstanding positive effects may account for a large share of the aggregated observed effect of democratization on GDP growth that is reported both in the original paper and by me in part 2.

4 (b)

In part 4 (a), I reported the distribution of the average estimated effect, but nothing is said about the statistical significance of those estimates. In this part, I show both the distribution of the estimates and the statistical significance using country-clustered standard errors. To get the standard errors I define the variable $\Delta y_c^{\bar{s}} = \frac{1}{5}\sum_{s=15}^{19} \Delta y_c^s$ (average GDP change 15-19 years after t_d) and use it as dependent variable to estimate the same equation as in part 4(a) for each event k. I present the results graphically in figure 6 and the descriptive statistics in Table 4. By comparing with table 3 we see that we get very similar results.

Table 4: Summary of Event-Estimates

	Obs.	Mean	Median	Std. Dev.
Average Effect 15-19 years	35	17.91	7.8	43.03

Then in figure 3 we see whether the estimates are statistically significant at the 95% level using country-clustered standard errors. According to our results, from 35 events, only 10 are statistically significant; 2 less than zero and 8 positive.

However, it is important to stress that this inference is incorrect. The reason is that the DID estimator β_{DID} is biased, and the size of the bias depends negatively on the number of treated units. In all these estimations in this part we are in the extreme case in which there is only one treated unit, which makes almost certain that the inference conclusions that arise from figure 6 are incorrect. Moreover, even the Conley-Taber method does not account from the heteroscedasticity that arises from differences in sample size. Ferman & Pinto (2019) inference technique for DID accounts for these two problems. However, I was unable to implement any of these two inference methods.

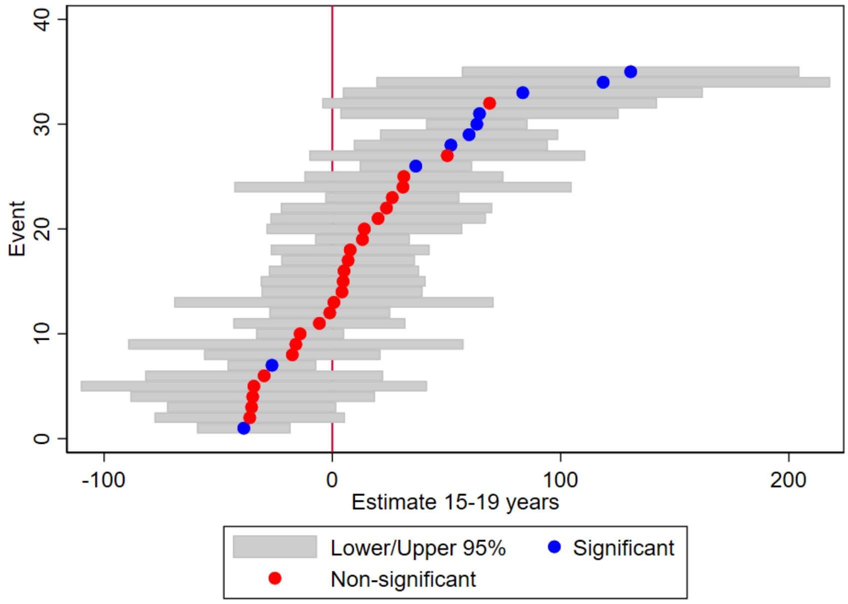

Figure 6: Distribution and significance of estimates

4 (c)

In this exercise I estimate a pooled diff-in-diff regression controlling for 4 GDP lags but including event fixed effects. In this setting, every event k consists of N_k observations, one for each country, with $N_k - 1$ consisting of the clean controls and 1 for the treated country. I redefine the variable $Event_k$, which now is equal to one for all N_k observations (countries that constitute event k) and zero otherwise. It is important to mention that, if more than one democratization took place in the same year (let's say countries i and g), then both treated countries will have exactly the same clean controls, so $Event_i$ and $Event_g$ will be collinear and omitted from the regression. The model equation I am estimating is:

$$\Delta y_c^s = \beta^s D_c + \sum_{l=1}^{4} \delta_l y_{t-l}^c + \sum_{k=1}^{K} \theta_k Event_k + \epsilon_c$$

Where K is the total number of events. I present my results in table 5 and graphically in figure 7. Table 5 only shows the results for $s \in [15, 19]$ and the average effect. The average is 16.780, which is at least 2.6 log points greater than the regression adjustment estimation in column 5 of (my) table 2.

Nevertheless, the result is quite similar to what we had before. It is also approximately 1.5 log points smaller than the average of the event-specific estimates (parts 4a and 4b). In figure 7 we see quite similar patterns to those specified in part 2. However, the greatest differences are that t$\hat{\beta}^s$ is only statistically different from zero for $s \in [22, 27]$

Table 5: 15-19 Years Effect with Event Fixed-Effects

	(1) 15 years	(2) 16 years	(3) 17 years	(4) 18 years	(5) 19 years	(6) Av.	(7) Av.(Bootstrap)
Avg. effect	15.955	12.299	19.699	17.335	18.612	16.780	16.780
on log GDP	(9.922)	(9.488)	(10.394)	(10.039)	(10.454)	(4.589)	(6.735)
N	1348	1292	1077	878	707		2642

approximately, and the maximum estimate is greater than in all other cases estimations. I understand that the logic of incorporating event fixed effect is to make each θ_k to capture every specificity of $Event_k$ (that is the comparison in GDP growth between a country that democratized and those who did not) so that β^s captures exclusively the effect of democratization.

Part 5

In this part I try an implementation of the Synthetic DID estimation. For practical purposes, I estimae the same equation as in part $4(c)$, with the only difference that I assign weights to every control unit, obtained by implementing the synthetic controls method. We consider two different specifications: one uses 4 and the other 10 GDP pre-treatment values as predictors (s1 and s2 herinafter). I get a vector of weights w_k for each event k, then we assign those weights to our stacked, wide dataset. Finally, I assign a weight equal to 1 to each treated country in the dataset, and implement the DID estimation with 4 lags for each s.

That is the abstract description. However, when implementing this technique, I had to eliminate controls for which we did not have at least 10 pre-periods GDP observations for each event k. The reason is that the *synth* command in Stata does not run when many donors lack the observations of the variables that are being used as predictors. I had to make a balance between (1) number of donors per event and (2) number of events available. The wide dataset that I use for the estimation only considers events for which the synthetic control method could be implemented. The results for the 2 specifications are displayed in figures 8 and 9

For specification 1, the shape of $\hat{\beta}(s)$ is very similar to all our (correct) previous estimations. However, the coefficient is never statistically different from zero. I am not able to tell whether this is due to the weighted nature of our regression, or to the fact that there are less observations being considered (due to the considerations specified above).

Figure 9 shows the results for the Synthetic DID using 10 GDP pre-treatment values as predictors. In contrast to all previous results, $\hat{\beta}(s)$ is an almost flat function around zero.

Figure 7: Synthetic DID: Specification 1

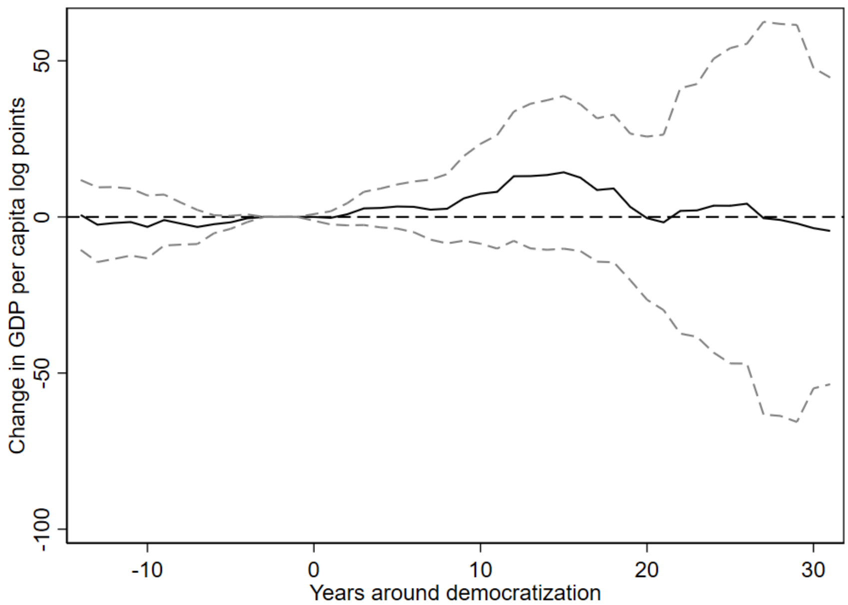

Figure 8: Synthetic DID: Specification 2