Econometrics fourth Assignment

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All the code of the assignment

GitHub

Question 1 RCT

a) Summary

"Engaging Teachers with Technology Increased Achievement," authored by Sabrin A. Beg, Adrienne M. Lucas, and Waqas Halim, explores the impact of technology integration on teacher engagement and student achievement. The research focuses on how providing teachers with access to technology tools and training can enhance their instructional practices and ultimately improve student outcomes. The study recognizes the potential of technology to revolutionize education by offering interactive and personalized e-learning experiences. By equipping teachers with the necessary skills and resources, the program aims to empower them to integrate technology into their teaching methods effectively.

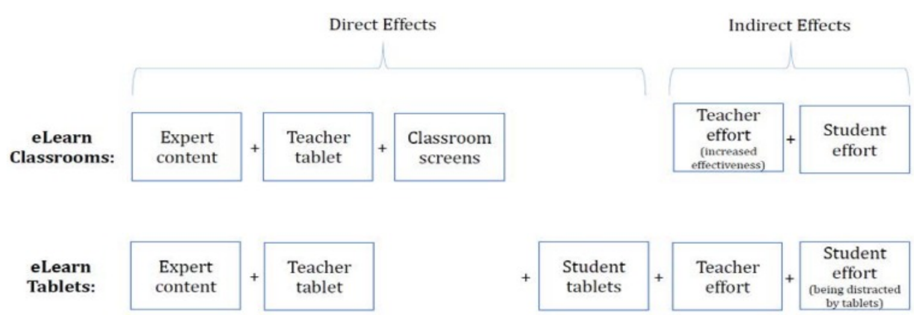


Figure 1: figure 2 of the paper

The strategy is a classic RCT where two relevant assistance programs are equipped with different interventions. On the one hand, the first program called "eLearn Classrooms" has classroom screens and a Teacher tablet. On the other hand, the second program replaces classroom screens with Student tablets and it is called "eLearn Tablets". The main purpose is to measure the effect of such interventions on academic performance and the authors compare both as different experiments with their own control group clearly using schools as intervention units.

As a theoretical framework, the authors mentioned that any intervention has two effects, a direct one which is the technological assistance, and an indirect one which is based on the agent's behavioral changes due to the intervention.

The identification strategy is simple and it can be studied through the next equation:

$$y_{is} = \alpha + \beta treatment_s + X'_{is}\Gamma + \epsilon_{is} \tag{1}$$

Where y is the output (grades for example), *treatment* is clearly the treatment and the rest are controls and errors, all variables indexed by i (student) and/or s (school). The intervention has surprising results because it does matter how exactly you provide the technology intervention. While the "eLearn Classrooms" is successful with a 0.3 standard deviations increase in test scores, the "eLearn tablets" decreased by 0.4 sd on the same test.

b) Summary statistics

This summary is mainly used to check if the Randomized Control trial is indeed randomized. It compares both, treated and control groups, in order to identify if there is any difference that could explain differences in outcome and is not related to the treatment itself.

Table 1: Summary Statistics

	eLearn Classrooms			eLearn Tablets		
	Treatment	Control	Difference T-C	Treatment	Control	Difference T-C
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Student Characteristics						
Combined Math and Science Score	-0.056 (0.99)	0.068 (1.01)	-0.12 (0.190)	0.019 (1.10)	-0.008 (0.96)	0.027 (0.28)
Age	13.90 (1.24)	13.87 (1.23)	0.03 (0.102)	12.12 (1.38)	12.17 (1.43)	-0.05 (0.13)
Days Absent Last Month	1.50 (2.41)	1.17 (1.79)	0.327* (0.173)	1.40 (2.03)	1.66 (3.40)	-0.25 (0.20)
Has a Computer at Home	0.43 (0.50)	0.41 (0.49)	0.02 (0.0484)	0.23 (0.42)	0.22 (0.41)	0.01 (0.06)
Mother Has No Formal Schooling	0.35 (0.48)	0.33 (0.47)	0.02 (0.0576)	0.36 (0.48)	0.44 (0.50)	-0.08 (0.07)
Father Has No Formal Schooling	0.17 (0.38)	0.20 (0.40)	-0.02 (0.0341)	0.22 (0.41)	0.26 (0.44)	-0.05 (0.05)
Panel B: Teacher Characteristics						
Has an Advanced Degree	0.75 (0.44)	0.80 (0.40)	-0.05 (0.0806)	0.62 (0.49)	0.67 (0.47)	-0.05 (0.12)
Years of Teaching Experience	10.72 (8.52)	10.67 (9.10)	0.05 (1.727)	15.03 (11.65)	14.52 (10.52)	0.51 (2.88)
Minutes per Day Planning Lessons	40.67 (33.75)	33.64 (27.85)	7.03 (5.477)	4.86 (12.80)	5.87 (12.85)	-1.01 (3.02)
Use Technology to Prepare for Class	0.58 (0.50)	0.60 (0.49)	-0.02 (0.106)	0.62 (0.49)	0.57 (0.50)	0.05 (0.14)
Use Technology in Class	0.14 (0.35)	0.17 (0.38)	-0.03 (0.0650)	0.48 (0.51)	0.47 (0.50)	0.01 (0.15)
Panel C: School Characteristics						
Total Enrollment in Grade	63.10 (16.36)	63.21 (13.52)	-0.11 (3.901)	60.1 (42.3)	52.1 (29.8)	7.97 (10.2)
Sections in Grade	1.40 (0.50)	1.35 (0.48)	0.06 (0.128)	1.55 (0.8)	1.40 (0.8)	0.15 (0.2)
School Has a Computer Lab	0.90 (0.31)	1.00 (0)	-0.100* (0.0557)	0.60 (0.5)	0.65 (0.5)	-0.05 (0.1)

Notes: * significant at 10%; ** significant at 5%; *** sig[illegible] Columns 1, 2, 4, 5: Standard deviations appear in parenthesis. Columns 3 and 6: Cluster-robust standard errors appear in parenthesis. Enrollment and number of sections for relevant grade: grade 8 for Classrooms and Grade 6 for Tablets.

Figure 2: table 1 of the paper

As you can see, there are only two characteristics that could be a problem. The authors are totally aware of this situation and they try to solve it through Lasso controls. These kind of controls will be explained some question below.

c) Attrition

The authors do find some kind of attrition because the eLearn classroom treatment implies more follow-up exam attendance in general. Since the control group is less likely to attend the exam maybe we could be overestimating the effect of the treatment since the treated group is more motivated and not because they were exposed to the program, this is an indirect effect and it could produce some biased conclusions. However, the research provides a credible explanation showing estimations of the worst and the best case scenario in the presence of this auto-selection, these estimations are called "Lee bounds".

Appendix Table A3: Lee (2009) Bounds

	Standardized Combined Project Math and Science Test			
	eLearn Classrooms		eLearn Tablets	
	Lower Bound	Upper Bound	Lower Bound	Upper Bound
	(1)	(2)	(3)	(4)
Treatment	0.271**	0.305**	-0.467***	-0.397***
	(0.127)	(0.134)	(0.155)	(0.152)
Observations	2,551	2,551	2,939	2,939

Notes : * significant at 10%; ** significant at 5%; *** significant at 1%. Standard errors clustered at the school level appear in parenthesis. Sample size adjusted for attrition following Lee (2009). Controls determined by LASSO.

Figure 3: Table A4 of the paper

Then, even when the estimations are biased they are most likely between those limits, and, for example, the "eLearn Classrooms" has a positive effect on test scores of at least 0.271 and at most 0.305 standard deviations even in the presence of auto-selection.

d) Possible identification issues

There are two possible issues, maybe a violation of SUTVA or imperfect compliance. In the first place, the standard unit of treatment values assumption (SUTVA) could be a problem if any of the treatments implemented in this research were implemented to students and not to the whole school. It could be a problem if maybe students of treated schools interact closely with control school's students but it's unlikely. In the second place, imperfect compliance could also be a problem as long as the treatment was not supervised, but it is clearly not the case in this research since is part of the data collected, even attendance was a relevant record and constantly monitored. In conclusion, those are not big problems to be worried about, in fact, the biggest problem in the experiment is the red squares in the Figure 2.

e) Lasso

In order to solve the problem found in the Figure 2 about the big differences between the control and treatment group the authors use Lasso as an approximation of the coefficients under the restriction of controls that are not allowed to predict substantially the outcome. Specifically:

"The PDS methodology uses the lasso estimator to select the controls. Specifically, the lasso is used twice: (1) estimate a lasso regression with y as the dependent variable and the control variables x1, x2, x3, ... as regressors; (2) estimate a lasso regression with d as the dependent variable and again the control variables x1, x2, x3, ... as regressors. The lasso estimator achieves a sparse solution, i.e., most coefficients are set to zero. The final choice of control variables to include in the OLS regression of y on d is the union of the controls selected in steps (1) and (2), hence the name "post-double selection" for the methodology." (Stata documentation)

If you control for predicted Lasso controls then you are controlling by the possible overreaction of the outcome caused by differences between treated and controls. However, like most Machine Learning procedures there is a bigger risk of bias since it is forcing better adjustment through restrictions in the OLS minimization, in exchange for less variance.

f) Interpretation of coefficients

Table 2 of the paper or its replication (replication table 2) shows the main results of the paper. The interpretation is direct from the coefficients as additional standard deviations because the treatment is a dummy variable. Then, for example, using the first column we know that the exposure to the "eLearn classrooms" implies scores 0.26 standard deviations bigger.

Question 2 IV

a) Summary

This research is mainly focused on explaining the origin of certain conflicts through Malthusian logic. The authors are in favor of that a bigger population eventually leads to scarce resources and therefore more frequency of violent events. However, if there are endogenous decisions in human history, one of the greatest examples would be the birth rate because there are several contributions indicating that the number of children in a home is determined by the economic environment. Then it is impossible to avoid circularity and the authors are well aware of this situation.

Part of the contribution is not only the quantitative results but also being useful as an example of a new shift-share instrument application. This research uses a predicted mortality instrument which is based on the idea that new treatments against different diseases are external shocks. Moreover, it is clear that a better health system implies more population levels because of the less mortality rates. This instrument will be explained in detail in the questions below.

The identification strategy is an instrumental variable with two stages least squares, as simple as they are it is pretty useful to explain this scenario. The outputs of interest are any measure of violent events, while the explanatory variables are several controls and the population variable which is based on the first stage. In this case, the studied agent are countries through time.

$$c_{it} = \pi x_{it} + \zeta_i + \mu_t + Z'_{it}\beta + \epsilon_{it} \tag{2}$$

Where c is some measure of conflict, x is log population and the rest are controls and fixed effects. The index i is for countries and obviously, t represents the year. As we said, the population level is endogenous and keeps circularity with conflicts, then the first stage is:

$$x_{it} = \phi M^I_{it} + \tilde{\zeta}_i + \tilde{\mu}_t + Z'_{it}\beta + u_{it} \tag{3}$$

Where M^I is the shift-share instrument.

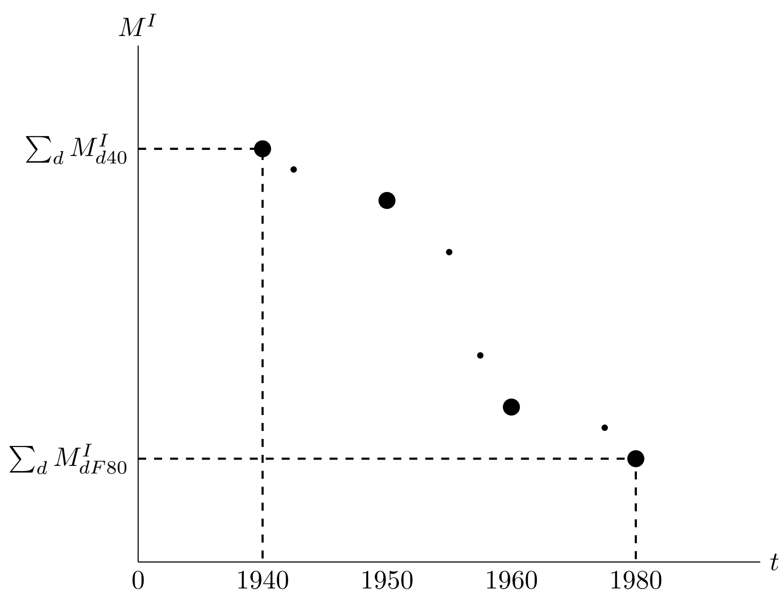
The conclusions are as the authors expected, more population implies more violent events or at least makes social conflicts more likely.

b) The shift-share instrument

The shift-share instrument has several dummies that indicate where we can turn off some parts of the sum to turn on other ones, building linear combinations that evolve through time. The particular case of the paper is:

$$M^I_{it} = \sum_{d \in D} ((1 - I_{dt})M_{di40} + I_{dt}M_{dFt}) \tag{4}$$

Let us fix a country i, then the equation above indicates the mortality rate in the year t as a linear combination of the aggregated mortality rate of different diseases in the 1940s and the same aggregated mortality rate but in the frontier date (which is assumed to be less than 1940s one because otherwise, the instrument has no sense at all). For example, again fixing the country, M^I_t should look like this (under the assumption that in 1940 none of the diseases have been treated and in 1980 all diseases have some treatment):



The instrument is certainly relevant, moreover, the instrument is said to be exogenous because *This measure is the sum of each country's initial (1940) mortality rate from infectious diseases until the moment of a global intervention (an innovation or campaign). After a global intervention occurs, the mortality* *rate from the diseases in question declines to the lowest or "frontier" mortality rate in our sample.* In other words, global innovations are out of the country's control.

c) First stage and falsification

Table three of the paper has two relevant roles, it is the first stage of the long differences model (1980 vs 1940) and it is the falsification exercise. We can build the estimated equation:

$$x_{it_1} = \phi M^I_{i1980} + \tilde{\zeta}_i + \tilde{\mu}_{1980} + Z'_{i1980}\beta + u_{it_1} \tag{5}$$

$$x_{it_0} = \phi M^I_{i1940} + \tilde{\zeta}_i + \tilde{\mu}_{1940} + Z'_{i1940}\beta + u_{it_0} \tag{6}$$

Then, looking for differences:

$$x_{it_1} - x_{it_0} = (\tilde{\mu}_{1980} - \tilde{\mu}_{1940}) + \phi(M^I_{i1980} - M^I_{i1940}) + (Z'_{i1980} - Z'_{i1980})\beta + (u_{it_1} - u_{it_0}) \tag{7}$$

Finally, we have:

$$\Delta x_{it_1,t_0} = \alpha + \phi \Delta M^I_{i1980,1940} + \tilde{\epsilon}_{it} \tag{8}$$

So we can also avoid using country-fixed effects. Moreover, if we set $t_1 = 1980$ and $t_0 = 1940$, then we have the first stage we were looking for. If we change the outcome (currently x is population as we wrote before) then we can fit the reduced form and, of course, if we change $t1$ and $t0$ we can make a falsification test.

Note that:

$$\partial x_{it_1,t_0} = \phi \partial M^I_{i1980,1940}$$

We can take this as a cross-county regression, and all marginal effects are interpreted approximately as $(100 * \exp \phi \partial M^I_{i1980,1940} - 1)\%$. Then, taking the first approximation of $\phi = -0.782$ we know that the population increases by about 45% when the mortality is 0.469 smaller or 0.469 survive per 100 people in 1980 with respect to 1940. All the coefficients can be found in replication table 3.

On the other side, the falsification tests are a way to avoid possible issues with critics based on the correlation between the instrument and preexisting trends in population and conflicts even before 1940. The authors test this issue by making a "falsification" test changing $t1$ and $t0$ from $t_1 = 1980$ and $t_0 = 1940$ to $t_1 = 1940$ and $t_0 = 1900$ expecting no statistically significant results. As they expected, this was indeed the case,*bolstering their confidence that the predicted mortality instrument is not capturing some other economic or political trends.*

d) Second stage

The interpretation of coefficients is as follows:

$$\partial y = \pi \partial log(pop)$$

$$\partial y = \pi \frac{\partial pop}{pop}$$

$$\partial y = \pi \frac{100 \partial pop}{pop} \frac{1}{100} = \pi \frac{\Delta \% pop}{100}$$

Therefore, if the population increases in 10% then, for example using column 1 of Panel A of replication table 4, the conflict increases in 0.0617 years of conflict or 0.617 years of conflict per decade. The interpretation is similar for the rest of the dependent variables, they play the role of robustness checks because two of them are the same measure but from different databases, and the last one is a measure of conflict but with fatal results (this particular one is also a logarithm, then its coefficient interpretation is an elasticity).

The interpretation for panel B is exactly the same as panel A, the big difference is that panel B has panel regressions because it uses 1940, 1950, 19060, 1970, and 1980 instead of the differences between 1980 and 1940 directly.

Over-identification test

This test is clearly unnecessary because all the paper is exactly identified.

Weak exogeneity test

This test, more commonly known as Hausman test, has its p-value in the last row of every model. Although the p-values are not as small as we would expect, at least every p-value is small whenever the variable of interest is statistically significant compared with those which are far from being accurate. This is a good sign because we are more likely to reject the possibility of a useless instrument whenever the instrumentalized variable is statistically significant, which makes a lot of sense. At a 10% significance level, we would reject that the OLS estimation is the same as 2SLS estimations in 3 of 10 cases, with 5% significance we would do so at 2 of 10 cases, with 1% at 1 of 10 cases, and so on.

Cragg-Donald

We know that testing if an instrument is weak or not, at least formally or directly, is impossible. However, the Cragg-Donal statistic could be a good approximation of a formal test. Moreover, in all cases, the statistic is bigger than its critical value of 10% significance proposed by Stock-Yogo (2005), in other words, the p-value of the Wald statistic would be at most 10% whenever we can reject a useless instrument.

e) Mexican data

This is literally the same identification strategy as before, 2SLS with some controls but now this is a within-country analysis because the agents or the index i is related to a Mexican municipality instead of a country, everything else remains the same.

Question 3 RD

a) Summary

This research is mainly focused on explaining how politicians' tenure or time in charge is directly associated with higher collusion probabilities. The main idea is that when a politician has been in charge for a long time then they have incentives to keep it that way by making good relations with local entities, for example, several services companies who are able to participate in public tenders to provide the locality. However, this kind of provider is not always the most efficient or the cheapest, even then they win in public tender procedures. Clearly, this is an endogenous relation, and the paper is totally aware of this situation, in order to solve it the authors propose an RD model.

To interpret the RD model we need a treatment assignment based on a clear discontinuity in some observable variable. In this case, the authors observe whether a mayor wins or loses an election, and those who win with a marginal difference are actually not so different from their opponent who finally loses. At the end of the day, such victories can be interpreted as an exogenous shock increasing the time in charge and therefore it could potentially affect public auction results because of the previous hypothesis. Moreover, as a second approach, the authors are concerned about an electoral reform made in March 1993 that could be used as another treatment measure that will be explained in detail in the last question.

The data is several outcomes of elections and procurement auctions in some Italy municipalities between 2000 and 2005. They study the number of bidders, the winning rebate (basically how much the tender process is able to reduce costs by selecting their respective winner and how much the winner takes to themselves), the probability that the winner is actually a local provider, and the probability that the same firm is awarded in more than one auction. All of them can shed light on some collusion patterns behind inefficient behaviors and unexpected changes in costs.

The results are significant and suggest that Italian municipalities are actually taking inefficient procurement processes because of their mayor and their interest conflicts between keeping their position and acting as public administrator. Their main findings *show that one additional term in office not only significantly reduces the number of bidders participating in the auctions (11.48 percent) but also reduces the winning rebate (5.7 percent).*

b) Figures of possible discontinuities

If the treatment marks a difference in the results of the auctions, then we should expect some kind of jump in such results based on the elections. Each treatment unit is an incumbent mayor in a municipality and the variable used to determine the cutoff in the treatment is the margin of victory measured as the percentage difference of votes with their opponent in the last election. On the other side, each observation also has a variable of interest that should be affected by the cutoff and it will present a discontinuity if we plot it together with the margin of victory. For example, we can see the number of bidders:

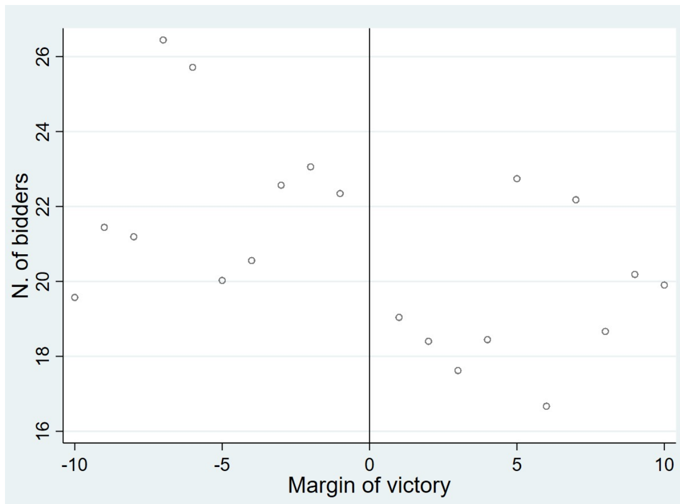


Figure 4: Observations

The cutoff is the line that marks victory or defeat, the positive Margin of victory represents victory and therefore an additional term in charge and the negative Margin of victory represents defeat and only one term in charge. Maybe we can see a discontinuity with only this information but it could be a challenge since we need to imagine a projection or tendency close to MV equal to zero. Instead of imagining it, we can simply add it, for example fitting a third-grade polynomial model:

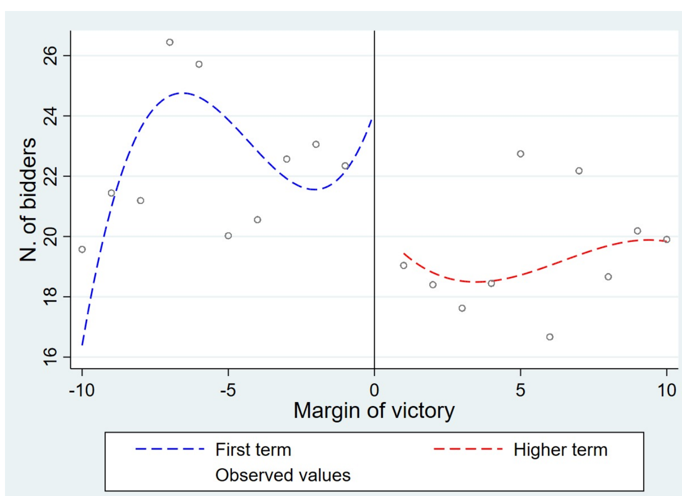


Figure 5: Third-grade polynomial

Or maybe it could be an option a mean smoothing line:

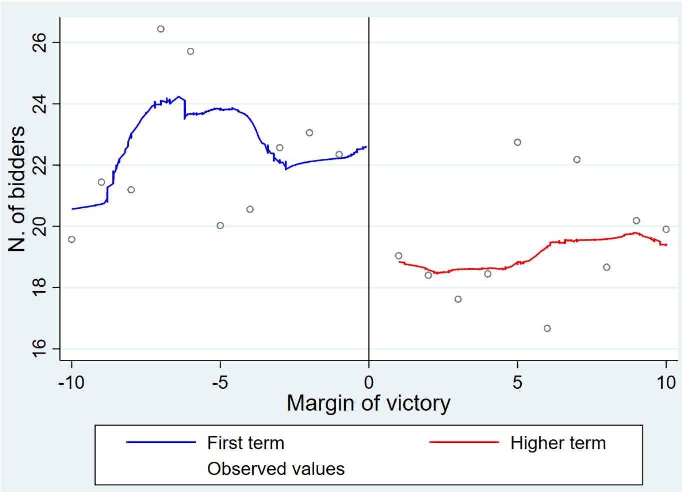
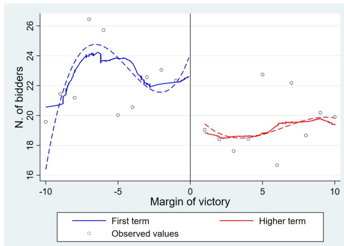
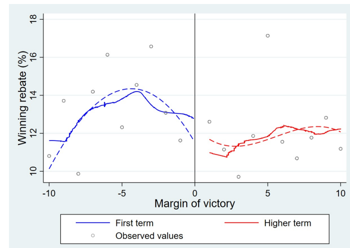


Figure 6: Mean smoothing

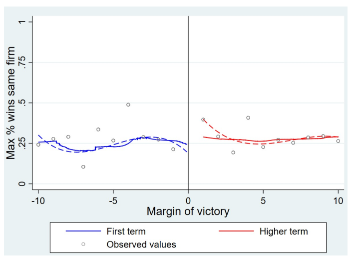
And now we can observe that there is a clear discontinuity and maybe we can predict an exact number, but we certainly can say that we are expecting a reduction in the number of bidders whenever the mayor's tenure is bigger. This is exactly the same information we need to study in the other three figures and even when the result is not as clear as we want, we still need to estimate the model (for example in (b) the discontinuity is questionable).



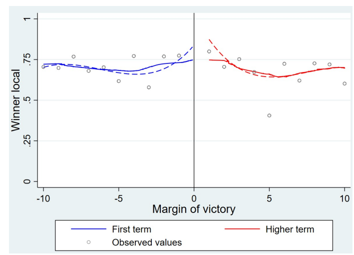
(a)



(b)



(c)



(d)

Figure 7: Replication Figure 1 of the paper

c) Assumptions or continuity in other variables

However, the discontinuity mentioned in the previous question can be interpreted as causality as long as other relevant variables don't change with this cutoff. Otherwise, we wouldn't know if the variable changing is changing because of the treatment or maybe because is related to the covariant which is also changing with the cutoff. As you can see in the next figure, at least at the municipality level, there is no significant change in the cutoff, this can be tested of course with a proper RD model.

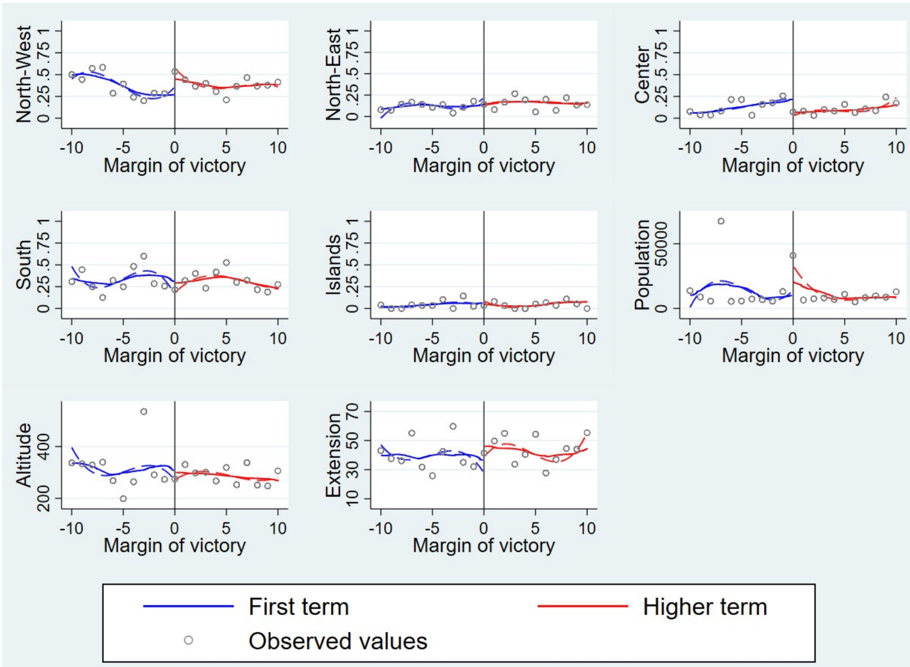


Figure 8: Caption

d) Results of RD

The RD is represented by the equation:

$$y_{im} = alpha + \beta T_{im} + g(MV_{im}) + \gamma TL_{im} + \delta_1 X_i + \delta_2 X_m + v_{im} \tag{9}$$

Where y is the outcome of interest, while T represents the treatment as the number of terms, moreover we have $g(MV)$ which is a third-degree polynomial fitting the cutoff variable. The indexes are i for auctions and m for mayors, and clearly, X are several controls. The most important coefficient is β because we will be able to see directly how an additional term in charge affects the outcomes of the auctions.

The replication of table 5 and replication of table 6 have the final results that are present in the research. Unfortunately, there are several of them that are not statistically significant as the estimated β in columns (1) and (3) of Table 5 and column (2) of Table 6, however, the rest are interesting findings and can be interpreted as a direct absolute change. Take into account, for example, that the fact that the mean number of bidders in all auctions is 21.52 tells us that an additional term in charge can reduce this number to -2.469 or, equivalently, a reduction of about -11.47%. In other words, this is a huge impact because it is well known in the auction literature that the best way to improve a tender procedure benefit for the principal is increasing the number of participants and not the other way around, therefore there are incentives beyond the reduction of costs.

e) McCrary

If there is some manipulation in the data maybe there are observations that have a strong frequency in one side of the cutoff when we plot their distribution over the victory margin. In simple words, it is possible that the election has some political consequences such that the participants are able to coordinate and negotiate their votes. This is an incredibly difficult process when the election has a massive scale, as a matter of fact, we have seen plenty of literature explaining that collusion becomes exponentially hard as the number of participants increases, a classic consequence of sequential games in microeconomics.

The McCrary test is as simple as effective because it uses the fact that we do not expect a discontinuity in the distributions of observations surrounding the cutoff. Given that this behavior shouldn't be present we test it using a graphic approximation. Literally, we have to build a histogram and then draw a line just above it such that it fits the estimated distribution. Then we can build a confidence interval around it to build a test in the cutoff as we can see in the next replication of the figure 2 in the paper:

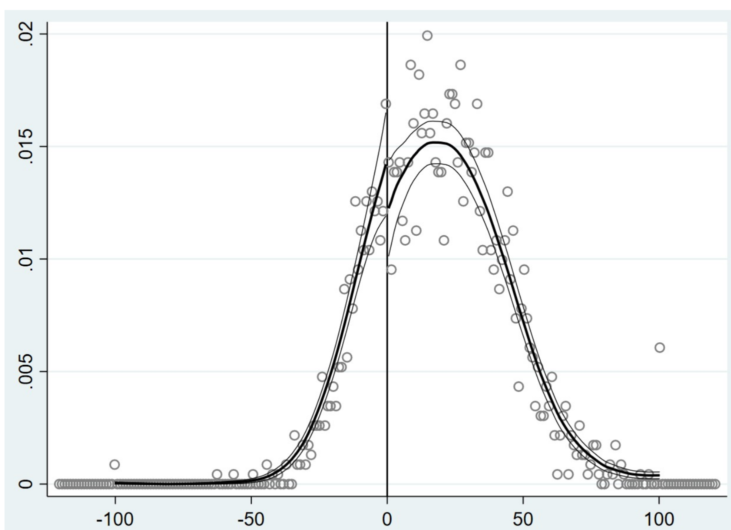


Figure 9: Margin of victory distribution

The line in the middle is the direct fit we talked about, while those two lines around it are the 95 percent confidence interval. The statistic of the difference in the cutoff is -0.18 with a standard deviation of 0.13, as we expected, not statistically strong enough to be concerned about manipulation. At least we have reasons to think there is no manipulation around the cutoff, however, we don't know if there is manipulation far from the cutoff, we can repeat the test making "false" cutoffs to look for other possible jumps, but since this is an election, that kind of test has no sense at all.

f) Results of RD with different polynomials

In fact, it could be a possibility that the estimations are sensible to the polynomial grade. Taking a look at the Table 5 with different degrees or Table 6 we can identify that coefficients that are statistically significant actually do not change that much, they are always similar. It can be accepted the fact that, actually, it does not matter the polynomial degree as long as this is able to produce something different than a straight line.

g) IV and RD (fuzzy-RD)

The authors explained that we already know that mayors elected for the first time before the reform could stay in office for two terms more (the treated group), while mayors elected for the first time after the reform could stay in office for only one term more (the control group). However, the reform also changed the mayor's electoral rule from party to individual ballot, a modification that could have induced a different selection among candidates because the new electoral system encouraged competition.

Clearly, this is a concern because it could introduce bias in the estimation due to the change of scenario. The author works under the assumption that this bias is minimal because all the mayors had gone through at least one individual ballot election between 2000 and 2005. Moreover, the research also mentioned the introduction of individual ballot elections probably had a delayed effect because of the difficulty for parties to find a candidate. Taking this as a fact, the authors excluded mayors elected immediately before and after 1993's reform, changing the paradigm to a fuzzy RD instead of a sharp one. Of course, the results are in the same line as the previously studied, so the authors were right in their intuition even when the treatment is unclear and only using a difference in probabilities.

Tables

RCT replication Table 2

	Panel A		Panel B (Lasso)	
	project	project+pec	project	project+pec
treatment	0.255	0.269*	0.270*	0.269*
	(1.90)	(2.27)	(1.99)	(2.29)
N	2622	2463	2622	2463

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

IV Replication Table 3

	First stage		Reduced form	
	Base sample	Low and Mid income countries	Base sample	Low and Mid income countries
	$\Delta logpop$	$\Delta logpop$	fraction in conflict	fraction in conflict
ΔM^I	-0.782***	-0.764***	-0.491**	-0.660**
	(-5.56)	(-4.00)	(-2.75)	(-2.80)
N	51	40	52	41
	Falsification			
	Base sample	Low and Mid income countries	Base sample	Low and Mid income countries
	fraction in conflict	fraction in conflict	$\Delta logpop$	$\Delta logpop$
ΔM^I	0.0854	0.197	-0.189	-0.198
	(1.56)	(1.56)	(-1.37)	(-1.01)
N	36	28	52	41

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

IV Replication Table 4

	Panel A Long differences 1980 vs 1940			
	COW	UCDP/PRIO	F&L	logdeathpop40U
logpop	0.617**	0.576*	0.879**	1.347*
	(2.90)	(2.42)	(2.90)	(2.25)
Cragg-Donald	21.582	22.533	22.533	22.533
Stock-Yogo 10% crit. val.	16.38	16.38	16.38	16.38
Weak exogeneity p-value	0.0719	0.1126	0.0058	0.2253
	Panel B Between 1980 and 1940			
logpop	0.609**	0.304	0.873	1.106*
	(2.96)	(1.21)	(1.89)	(2.44)
Cragg-Donald	32.756	34.388	34.388	31.823
Stock-Yogo 10% crit. val.	16.38	16.38	16.38	16.38
Weak exogeneity p-value	0.0331	0.972	0.116	0.3292

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

IV Replication Table 11

	Dependent variable is violent protests (Panels A and C) and log population (Panel B)								
	Panel A 2SLS								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
logpop	12.37**	13.33**	12.81**	13.10**	12.39*	13.00**	14.26**	10.95*	13.05*
	(3.19)	(3.02)	(2.88)	(2.71)	(2.45)	(2.92)	(2.79)	(2.20)	(2.05)
logpop40			0.621*						-0.108
			(2.14)						(-0.29)
primary_schooling40				22.07*					22.47*
				(2.51)					(2.06)
university40					161.5				3.572
					(1.13)				(0.03)
battles_centroid40						3.021**			1.746
						(2.74)			(1.47)
share_basin40							-0.617		-0.558
							(-0.57)		(-0.38)
share_ind40								-1.818	-1.029
								(-1.37)	(-0.70)
	Panel B First stage								
index_mean	-0.284***	-0.262***	-0.259***	-0.247***	-0.236***	-0.259***	-0.240***	-0.246***	-0.211***
	(-9.53)	(-8.82)	(-8.70)	(-8.44)	(-7.96)	(-8.72)	(-7.60)	(-8.74)	(-6.78)
	Panel C OLS estimates								
corr_logpop	4.700***	4.780***	4.700***	4.469***	5.163***	4.577***	4.748***	6.152***	5.132***
	(5.59)	(5.60)	(5.58)	(5.08)	(5.65)	(5.38)	(5.53)	(5.96)	(4.81)
N	4752	4752	4752	4128	4176	4752	4752	3760	3572

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

RD Replication Table 5

	(1)	(2)	(3)	(4)
	n_firms_bid	n_firms_bid	reb_final	reb_final
terms	-1.866	-2.469**	-0.903	-0.705*
	(-1.00)	(-2.65)	(-1.66)	(-2.29)
term limit binding		3.740*		1.181*
		(2.18)		(2.37)
population		0.0900***		0.0312***
		(3.58)		(8.43)
starting_value		0.746***		0.104***
		(8.03)		(6.28)
female		0.00572		0.146
		(0.01)		(0.47)
age		0.0354		0.0246*
		(1.16)		(2.44)
terms_party		-0.885		-0.103
		(-1.52)		(-0.54)
N	12687	12687	12687	12687

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

RD Replication Table 6

	(1) Local winner	(2) Local winner	(3) wins same firm	(4) wins same firm
terms	4.776*	3.458	6.023**	5.729**
	(2.48)	(1.59)	(3.24)	(2.62)
term limit binding		-1.604		-2.491
		(-0.48)		(-0.88)
population		0.00309		-0.108*
		(0.21)		(-2.47)
starting_value		-0.992***		-0.157***
		(-9.45)		(-4.33)
gender		3.035		-4.637*
		(1.75)		(-2.52)
age		-0.0778		-0.222***
		(-1.04)		(-3.33)
terms_party		0.552		1.367
		(0.41)		(1.19)
N	12687	12687	11099	11099

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

RD Replication Table 5 polonium

	Pol. Grade 2				Pol. Grade 4			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	n_firms_bid	n_firms_bid	reb_final	reb_final	n_firms_bid	n_firms_bid	reb_final	reb_final
terms	-1.840	-2.414**	-0.844	-0.714*	-2.515	-2.448**	-1.172	-0.761*
	(-1.07)	(-2.60)	(-1.57)	(-2.32)	(-1.21)	(-2.61)	(-1.89)	(-2.47)
term limit binding		3.422*		1.231*		3.790*		1.044*
		(2.15)		(2.53)		(2.10)		(2.03)
population		0.0898***		0.0313***		0.0901***		0.0310***
		(3.57)		(8.46)		(3.57)		(8.33)
starting_value		0.745***		0.104***		0.746***		0.104***
		(8.02)		(6.28)		(8.03)		(6.27)
female		-0.00415		0.148		0.0113		0.131
		(-0.00)		(0.48)		(0.01)		(0.43)
age		0.0364		0.0244*		0.0356		0.0241*
		(1.19)		(2.43)		(1.16)		(2.38)
terms_party		-0.905		-0.0999		-0.882		-0.110
		(-1.55)		(-0.52)		(-1.52)		(-0.57)
N	12687	12687	12687	12687	12687	12687	12687	12687

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

RD Replication Table 6 polonium

	Pol. Grade 2				Pol. Grade 4			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Local winner	Local winner	wins same firm	wins same firm	Local winner	Local winner	wins same firm	wins same firm
terms	4.459*	3.419	5.056**	5.831**	5.360**	3.901	6.787***	5.738**
	(2.37)	(1.57)	(2.75)	(2.66)	(2.70)	(1.80)	(3.34)	(2.60)
term limit binding		-1.378		-3.371		-0.521		-2.457
		(-0.43)		(-1.23)		(-0.15)		(-0.86)
population		0.00321		-0.112*		0.00473		-0.108*
		(0.21)		(-2.55)		(0.32)		(-2.46)
starting_value		-0.992***		-0.159***		-0.990***		-0.157***
		(-9.46)		(-4.35)		(-9.46)		(-4.33)
female		3.042		-4.666*		3.155		-4.634*
		(1.76)		(-2.53)		(1.82)		(-2.52)
age		-0.0786		-0.219**		-0.0737		-0.222***
		(-1.05)		(-3.29)		(-0.98)		(-3.31)
terms_partyt		0.567		1.310		0.604		1.367
		(0.43)		(1.14)		(0.45)		(1.19)
N	12687	12687	11099	11099	12687	12687	11099	11099

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$