

Micro-level institutions

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February 22, 2016

Introduction

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 - ▶ Countries that did or did not have successful assassinations attempts.
 - ▶ Countries that did or did not have leaders that died in office.
 - ▶ Countries that experienced different forms of colonialism due to differing rates of settler mortalities.
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An intuitive example

- ▶ Let's consider an example close to the heart of students: the legal drinking age in the U.S. is 21 years.
- ▶ Imagine (a stretch, I know) that this limit was perfectly enforced.
- ▶ If you had a population of young people nearing their 21st birthday, no one would be drinking the day before their birthday; the day after, some proportion of the population would be consuming alcohol.
- ▶ If you were interested in estimating the impact of alcohol on car accidents, you could compare the frequency of accidents among individuals one day after their 21st birthday to the frequency among individuals one day before their 21st birthday.

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An intuitive example, continued

- ▶ Why does this make sense?
- ▶ Are there significant differences between people one day after their 21st birthday and one day before that birthday, **other** than their legal drinking status?
- ▶ Unlikely; if we do observe a difference in accident rates between people slightly younger than 21 and people slightly older than 21, it seems reasonable to attribute this to the impact of alcohol.
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Notational framework

- ▶ Assignment to the treatment is going to be determined fully or partially by the value of a predictor (the covariate X_i); in the preceding example, this was age.
- ▶ D_i denotes treatment status.

$$D_i = \begin{cases} 1 & \text{if } X_i \geq X_0 \\ 0 & \text{if } X_i < X_0 \end{cases}$$

- ▶ The crucial point is that X_0 is a threshold; no matter how close X_i gets to the threshold, treatment status does not change until it has crossed the threshold.

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Simple model

- ▶ Suppose that potential outcomes can be described by this simple model: Y is linear in X , and the effect of treatment is constant.

$$E[Y_{0i}|X_i] = \alpha + \beta X_i$$

$$Y_{1i} = Y_{0i} + \rho$$

- ▶ This leads to a simple regression equation:

$$Y_i = \alpha + \beta X_i + \rho D_i + \epsilon_i$$

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Simple model, Part II

- ▶ RD captures causal effects by distinguishing the nonlinear and discontinuous function, $1(X_i \geq X_0)$, from the smooth function x_i .
- ▶ If the trend relationship is nonlinear, i.e. $E[Y_{0i}|X_i] = f(X_i)$, then we can construct RD estimates by fitting the following equation:

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Identifying assumption 1

- ▶ The first identifying assumption is that conditional on X_i , D_i is uncorrelated with Y_{1i} and Y_{0i} (potential outcomes with and without treatment).
 - ▶ In the sharp RD case, this is true by assumption: X_i fully determines D_i , thus there is no residual variation in D_i after conditioning on X_i .
 - ▶ Given your age, there is no variation in whether or not you are legally 21; you are or are not!
 - ▶ This assumption could be violated if individuals can manipulate their status vis-a-vis their threshold: i.e., if some individuals misrepresent their age in order to drink.
 - ▶ In that case, X_i (true age) does not fully determine D_i (legal drinking status), because some individuals are cheating.

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Identifying assumption 2

- ▶ The second identifying assumption is that the functions $E[Y_{1i}|X_i]$ and $E[Y_{0i}|X_i]$ are continuous at the threshold X_0 .
- ▶ Intuitively? Y_i may change with X_i .
- ▶ In our example, the number of accidents generally declines with age, both for drinkers and not-drinkers.
- ▶ Key assumption: the probability of an accident for a drinker does not jump discontinuously at the 21st birthday, and neither does the probability of an accident for a non-drinker.

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When, and why, is regression discontinuity useful?

- ▶ Regression discontinuity is useful when an outcome of interest changes discretely at a specified threshold.
- ▶ In addition to the previous example, consider test score thresholds for admission; eligibility for government programs defined by age; physical boundaries of towns defining eligibility for schools; etc.
- ▶ If the assumptions of an RD design are satisfied, then essentially you have a RCT around the threshold: all those close to the threshold (e.g., all those close to the age of 21) are similar in unobservable and observable characteristics; it is a matter of chance (**quasi-random**) that some pass their 21st birthday a few days earlier.
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Long-run effects of the Peruvian *mita*: overview

- ▶ This paper also seeks to analyze the role that historical institutions play in determining current underdevelopment, with two notable differences.
- ▶ First, it will use local evidence: comparing adjacent villages separated by a specific boundary line.
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Understanding institutional persistence

- ▶ Remember AJR found that settler mortality shaped early institutions; institutions persisted, and then affected economic outcomes today.
- ▶ The authors don't elaborate about the channels through which institutions are persistent: clearly, it is not literally true that governance structures are identical today to the colonial period.
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Estimation strategy

- ▶ The estimation strategy in this case is econometrically sophisticated; we will focus on understanding the core specification and the results.
- ▶ The primary equation of interest (equation 1 in the paper) is the following:

$$c_{idb} = \alpha + \gamma mita_d + X'_{id}\beta + f(\text{geographic location}_d) + \phi_b + \epsilon_{idb}$$

- ▶ Notation: c is an outcome of interest for observation i in district d along boundary segment b ; $mita_d$ is a dummy equal to one if the village was subject to the *mita*, and zero otherwise; $X'_{id}\beta$ and ϕ_b are control variables; and f is a flexible polynomial controlling for geographic location.

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Estimation strategy, part II

- ▶ Note in this case the threshold variable is geography (analogous to age in our example); rather than controlling for geography linearly, she uses a polynomial. More details about this in the paper.
- ▶ Return to the identifying assumptions.
 - ▶ Conditional on geography, potential outcomes are uncorrelated with *mita* status (i.e., no manipulation at the boundary).
 - ▶ All relevant variables enter their treatment (assignment to *mita*) with the same functional form on both sides of the boundary.
- ▶ The author presents some evidence consistent with these assumptions in Table 1: there don't seem to be significant differences in pre-treatment characteristics at the boundary.

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Summary statistics

TABLE I
SUMMARY STATISTICS^a

	Sample Falls Within											
	<100 km of <i>Mita</i> Boundary			<75 km of <i>Mita</i> Boundary			<50 km of <i>Mita</i> Boundary			<25 km of <i>Mita</i> Boundary		
	Inside	Outside	s.e.	Inside	Outside	s.e.	Inside	Outside	s.e.	Inside	Outside	s.e.
GIS Measures												
Elevation	4042	4018	[188.77] (85.54)	4085	4103	[166.92] (82.75)	4117	4096	[169.45] (89.61)	4135	4060	[146.16] (115.15)
Slope	5.54	7.21	[0.88]* (0.49)***	5.75	7.02	[0.86] (0.52)**	5.87	6.95	[0.95] (0.58)*	5.77	7.21	[0.90] (0.79)*
Observations	177	95		144	86		104	73		48	52	
% Indigenous	63.59	58.84	[11.19] (9.76)	71.00	64.55	[8.04] (8.14)	71.01	64.54	[8.42] (8.43)	74.47	63.35	[10.87] (10.52)
Observations	1112	366		831	330		683	330		329	251	
Log 1572 tribute rate	1.57	1.60	[0.04] (0.03)	1.57	1.60	[0.04] (0.03)	1.58	1.61	[0.05] (0.04)	1.65	1.61	[0.02]* (0.03)

(Continues)

Summary statistics, cont.

TABLE I—Continued

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	Inside	Outside	s.e.	Inside	Outside	s.e.	Inside	Outside	s.e.	Inside	Outside	s.e.
% 1572 tribute to												
Spanish Nobility	59.80	63.82	[1.39]*** (1.36)***	59.98	63.69	[1.56]** (1.53)**	62.01	63.07	[1.12] (1.34)	61.01	63.17	[1.58] (2.21)
Spanish Priests	21.05	19.10	[0.90]** (0.94)**	21.90	19.45	[1.02]** (1.02)**	20.59	19.93	[0.76] (0.92)	21.45	19.98	[1.01] (1.33)
Spanish Justices	13.36	12.58	[0.53] (0.48)*	13.31	12.46	[0.65] (0.60)	12.81	12.48	[0.43] (0.55)	13.06	12.37	[0.56] (0.79)
Indigenous Mayors	5.67	4.40	[0.78] (0.85)	4.55	4.29	[0.26] (0.29)	4.42	4.47	[0.34] (0.33)	4.48	4.42	[0.29] (0.39)
Observations	63	41		47	37		35	30		18	24	

^aThe unit of observation is 20 × 20 km grid cells for the geospatial measures, the household for % indigenous, and the district for the 1572 tribute data. Conley standard errors for the difference in means between *mita* and non-*mita* observations are in brackets. Robust standard errors for the difference in means are in parentheses. For % indigenous, the robust standard errors are corrected for clustering at the district level. The geospatial measures are calculated using elevation data at 30 arc second (1 km) resolution (SRTM (2000)). The unit of measure for elevation is 1000 meters and for slope is degrees. A household is indigenous if its members primarily speak an indigenous language in the home (ENAH0 (2001)). The tribute data are taken from Miranda (1583). In the first three columns, the sample includes only observations located less than 100 km from the *mita* boundary, and this threshold is reduced to 75, 50, and finally 25 km in the succeeding columns. Coefficients that are significantly different from zero are denoted by the following system: *10%, **5%, and ***1%.

Results - Living standards

TABLE II
LIVING STANDARDS^a

Sample Within:	Dependent Variable						
	Log Equiv. Household Consumption (2001)			Stunted Growth, Children 6-9 (2005)			
	<100 km of Bound. (1)	<75 km of Bound. (2)	<50 km of Bound. (3)	<100 km of Bound. (4)	<75 km of Bound. (5)	<50 km of Bound. (6)	Border District (7)
	Panel A. Cubic Polynomial in Latitude and Longitude						
<i>Mita</i>	-0.284 (0.198)	-0.216 (0.207)	-0.331 (0.219)	0.070 (0.043)	0.084* (0.046)	0.087* (0.048)	0.114** (0.049)
R^2	0.060	0.060	0.069	0.051	0.020	0.017	0.050
	Panel B. Cubic Polynomial in Distance to Potosí						
<i>Mita</i>	-0.337*** (0.087)	-0.307*** (0.101)	-0.329*** (0.096)	0.080*** (0.021)	0.078*** (0.022)	0.078*** (0.024)	0.063* (0.032)
R^2	0.046	0.036	0.047	0.049	0.017	0.013	0.047
	Panel C. Cubic Polynomial in Distance to <i>Mita</i> Boundary						
<i>Mita</i>	-0.277*** (0.078)	-0.230** (0.089)	-0.224** (0.092)	0.073*** (0.023)	0.061*** (0.022)	0.064*** (0.023)	0.055* (0.030)
R^2	0.044	0.042	0.040	0.040	0.015	0.013	0.043
Geo. controls	yes	yes	yes	yes	yes	yes	yes
Boundary F.E.s	yes	yes	yes	yes	yes	yes	yes
Clusters	71	60	52	289	239	185	63
Observations	1478	1161	1013	158,848	115,761	100,446	37,421

Challenge to these results

- ▶ What if the mita and non-mita districts were already different?
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Pre-mita characteristics

TABLE V
1572 TRIBUTE AND POPULATION^a

	Dependent Variable							
	Log Mean Tribute (1)	Share of Tribute Revenues				Percent		
		Spanish Nobility (2)	Spanish Priests (3)	Spanish Justices (4)	Indig. Mayors (5)	Men (6)	Boys (7)	Females (8)
Panel A. Cubic Polynomial in Latitude and Longitude								
<i>Mita</i>	0.020 (0.031)	-0.010 (0.030)	0.004 (0.019)	0.004 (0.010)	0.003 (0.005)	-0.006 (0.009)	0.011 (0.012)	-0.009 (0.016)
<i>R</i> ²	0.762	0.109	0.090	0.228	0.266	0.596	0.377	0.599
Panel B. Cubic Polynomial in Distance to Potosí								
<i>Mita</i>	0.019 (0.029)	-0.013 (0.025)	0.008 (0.015)	0.006 (0.009)	-0.001 (0.004)	-0.012 (0.008)	0.005 (0.010)	-0.011 (0.012)
<i>R</i> ²	0.597	0.058	0.073	0.151	0.132	0.315	0.139	0.401
Panel C. Cubic Polynomial in Distance to <i>Mita</i> Boundary								
<i>Mita</i>	0.040 (0.030)	-0.009 (0.018)	0.005 (0.012)	0.003 (0.006)	-0.001 (0.004)	-0.011 (0.007)	0.001 (0.008)	-0.008 (0.010)
<i>R</i> ²	0.406	0.062	0.096	0.118	0.162	0.267	0.190	0.361
Geo. controls	yes	yes	yes	yes	yes	yes	yes	yes
Boundary F.E.s	yes	yes	yes	yes	yes	yes	yes	yes
Mean dep. var.	1.591	0.625	0.203	0.127	0.044	0.193	0.204	0.544
Observations	65	65	65	65	65	65	65	65

^aThe dependent variable in column 1 is the log of the district's mean 1572 tribute rate (Miranda (1583)). In columns 2–5, it is the share of tribute revenue allocated to Spanish nobility (*encomenderos*), Spanish priests, Spanish justices, and indigenous mayors (*caciques*), respectively. In columns 6–8, it is the share of 1572 district population composed of males (aged 18–50), boys, and females (of all ages), respectively. Panel A includes a cubic polynomial in longitude and latitude, panel B includes a cubic polynomial in Euclidean distance from the observation's district capital to Potosí, and panel C includes a cubic polynomial in Euclidean distance to the nearest point on the *mita* boundary. All regressions include geographic controls and boundary segment fixed effects. The samples include districts whose capitals are less than 50 km from the *mita* boundary. Column 1 weights by the square root of the district's tributary population and columns 6–8 weight by the square root of the district's total population. 66% of the observations are from *mita* districts. Coefficients that are significantly different from zero are denoted by the following system: *10%,

Discussion questions - econometrics

- ▶ Do you find the identification strategy to be compelling? Do you believe there are other differences between communities inside and outside of the mita that could be a source of bias?
- ▶ What about external validity? (What is the definition of external validity)?
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- ▶ What channels does Dell posit are important in the long-term influence of the *mita*? Do you believe those channels? Could there be others that you believe are relevant?
- ▶ What outcome variables are used to measure the impact of the *mita*? Do you find these to be useful variables, or would you like to see others?
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- ▶ They define a measure of Holocaust severity.

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where N_i is a Nazi occupation dummy, and J and L denote the Jewish and total population in 1939.

- ▶ They refer to this variable as the **potential** impact of the Holocaust.
- ▶ Why do they use this measure, rather than the true impact of the Holocaust?

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- ▶ Institutions is a broad and all-encompassing term, and the historical and geographical settings we examined were diverse - autocracies and democracies, colonialized societies, centrally planned economies, and nations at war.
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Spatial formulations of majority rule

- ▶ Assume a group of voters has to pick a point on a line: e.g., a income tax rate between 0 and 100.
- ▶ Imagine each individual has a most-preferred point on the line, and preferences that decline as points further in either direction are taken up.
- ▶ Each individual has a bliss point, denoted x_i , and preferences are assumed to be single peaked.
- ▶ Definition: alternatives under consideration can be represented as points on a line, and each of the utility functions representing preferences has a maximum on the line and slopes away from the maximum on other side.

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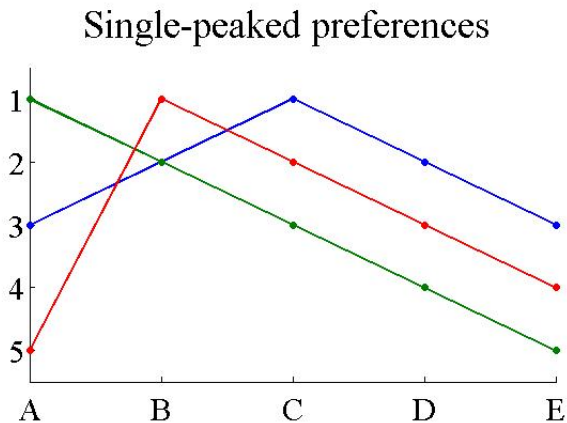
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Single-peaked preferences



Defining win set

- ▶ For each point y on the line, define the winset of y as $W(y)$.
- ▶ Let M be the set of majorities in the group; the winset is the set of points that some majority in M prefers to y .
- ▶ Intuitively: every point in the winset can plausibly beat y in a majority vote.
- ▶ In our example: B is in the winset of A , because both red and blue prefer B to A .
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