A Work Project, presented as part of the requirements for the Award of a Master's degree in Economics from the Nova School of Business and Economics.

DOES ALIGNMENT WITH RULING PARTY AFFECT EDUCATION OUTCOME? EVIDENCE FROM TANZANIA

MATTEO CORTESI

Work project carried out under the supervision of:

Professor Wayne Sandholtz

16/12/2022

Abstract

Combining 2015 ward-level elections and PSLE test scores data, this work examines the impact of Tanzanian ruling party alignment on education outcomes across Tanzanian wards. The methodology implemented is the Sharp Regression Discontinuity Design leveraging close elections, with education outcome as dependent variable, CCM election victory as treatment and margin of victory as assignment variable. Considering estimates for the four years after the elections, we find no significant effects on pupils' school performances in wards locally governed by CCM if compared to students in wards not aligned with the ruling party.

Keywords: Ruling Party, Election Results, CCM, Test Scores, Education, Regression Discontinuity

This work used infrastructure and resources funded by Fundação para a Ciência e a Tecnologia (UID/ECO/00124/2013, UID/ECO/00124/2019 and Social Sciences DataLab, Project 22209), POR Lisboa (LISBOA-01-0145-FEDER-007722 and Social Sciences DataLab, Project 22209) and POR Norte (Social Sciences DataLab, Project 22209).

1. Introduction

The passage from an autocratic single-party government to a multiparty regime can represent an arduous challenge for a country. The introduction of a multi-party democracy not always corresponds indeed to an improvement of economic policies, since a democratic government could be less incentivized to provide public services for the population (Stasavage 2005). Furthermore, we learn that the presence of a strong and deeply consolidated party can have a decisive impact on the development of the country[1]. The main Tanzanian party, CCM, has ruled the country since the independence, achieving promising results, such as reduction of poverty and economic growth (Treichel, 2005). Since the advent of democracy, many contend that CCM politicians engage in clientelism to forge enduring bonds with people (Tsubura 2015), in return of higher incentives, often restricted to the areas that support the ruling party.

This study aims to investigate the impact that Tanzanian elections have on education outcomes comparing the scores of PSLE standardized test from 2016 to 2019. We implement a Sharp Regression Discontinuity design (Imbens and Lemieux 2008; Cattaneo, Idrobo and Titiunik 2019) on ward-level electoral results and PSLE scores. As in Hyytinen et al. (2018), that examine the consistency of the RD design in close elections, we want to investigate whether pupils who attend schools in wards where CCM barely won achieve noticeably higher test scores in the standardized test, assuming that wards where CCM barely won the elections are on average comparable *ex ante* to district where it barely lost (Lee 2001). We consider under treatment condition the wards where the ruling party won the elections, and we use the margin of victory of the elections to compare the outcomes between treated and control groups around the cut-off. In particular, we find no statistically significant evidence that students in wards ruled by CCM achieve slightly higher grades from 2016 to 2019.

[1] Knutsen (2018) investigates economic growth among autocracies, testing if the variation in growth is higher in autocracies than in democracies.

It must be noted that, due to data limitations, we cannot expand the study to include all wards and students. Therefore, we concentrate our research on the wards where we were able to pinpoint the exact party that won the elections, that are displayed in Figure 1 in the Data section.[2]

2. Literature review

The economic literature devotes a special focus on the relationship between clientelism, autocratic parties and social policies, with regards to developing countries and new democracies. The partisan bias, that affects country-level resource allocation in autocratic and clientelist regimes, have been documented by Ansolabehere and Snyder (2003), that examine the relationship between the American ruling party and the distribution of public funds across the states. In particular, they find that states where the ruling party has higher level of electoral support receive on average more public funds that states of greater support for the opposition. Brollo and Nannicini (2011) implement a Regression Discontinuity design to estimate the effect of political alignment with the ruling party on federal transfers within Brazilian municipalities. They reveal that municipalities where the opposition won by a narrow margin receive fewer federal transfers than municipalities ruled by the same party as the Brazilian government. Similar results are documented by Jensenius and Chhibber (2014), that investigate Indian political environment to provide evidence that the government allocates development funds to areas of greater support of the ruling party.

Macdonald (2014) focuses his research on Zambian elections and Zambian political environment, that represents one of the recent emerging democracies in Africa. Through a Regression Discontinuity approach, he estimates the effect of the incumbency status on the

[2] We successfully mapped 2119 wards in which CCM won and 823 in which the opposition won. In grey all the 702 wards for which we did not have precise information, or they are discordant between sources.

probability of winning the elections. In contrast to the previous studies, he finds evidence of incumbency disadvantages during national elections in Zambia, owing primarily to the impossibility of establishing an autocratic and united coalition through vote and media manipulation.

Paget (2021) conducts research on the authoritarian and autocratic tendencies of the former Tanzanian President Magufuli after 2015 elections. He provides example of measures aimed to ensure political and social control over the population, such as suspensions of newspaper or police ban imposed on public meetings. Through the years of his mandate, Magufuli shows intolerance of the opposition party and public dissent, using his authority to limit the freedom of expression of individuals over the country, especially in the press. On the other hand, as a supporter of the free education programs implemented in Tanzania by CCM, he plays a central role in the realization of the *Free Secondary Education* program.

Given the predominant influence that CCM has on the country and the autocratic behavior of the president, we want to investigate if free education programs guarantee uniform results across the country regardless of politics, or if areas of greater support for the ruling party experienced higher outcomes. A study focused on the relation between clientelism, democracy and education in the developing context is Abdulai and Hickey (2016). In their paper, they examine how resources were allocated in Ghana's education sector between 1993 and 2008. Their research is centered on public education spending in a country characterized by inequalities between northern and southern regions with regards to education. Analyzing the distribution of power within ruling coalitions and per capita educational expenditures in the different regions of the country, they show that the ruling parties have been able to allocate more resources to their regions. Akhtari, Moreira and Trucco (2022) investigate how political turnover in Brazilian mayoral elections affects local governments' provision of public services. Leveraging close election results, they focalize on education outcomes in municipalities where the local government changed. They find that pupil's achievement is negatively affected by political turnover in municipal schools, while the turnover has no effect on schools not controlled by the ruling party.

Our thesis is closely related with this particular branch of the relationship between autocratic governments and resource allocation. By assessing how the result of ward-level elections affects education outcomes, the specific research question of interest is whether students in wards politically aligned with the ruling party achieve better school performances in the years after the elections than students in wards where the opposition won the elections. This hypothesis, in line with previous studies, would allow us to determine whether there are disparities in free education provision across Tanzanian wards. We expect indeed that the impact of the programs on outcomes is different, depending on the alignment with the national ruling party.

3. Historical background

3.1. Tanzanian political environment

Tanzania has been ruled by the same party since its independence from the United Kingdom. *Chama Cha Mapinduzi* (CCM)[3], founded officially in 1977, has governed without an opposition until 1992, when a multy-party regime was formally settled in the country, led by *Chama Cha Demokrasia na Maendeleo* (CHADEMA). However, CCM kept its authoritarian structure, and the development of the country was strictly related to the development of the party (Paget 2021). CCM domain is evident when analyzing the results of the elections in 2005, when the electoral victory of CCM was so crushing[4] that it was questioned the usefulness of a multi-party regime in a system that was clearly one-party driven (Nyang'oro 2006). Looking at

[3] In English stands for "*Party of the Revolution*".
[4] CCM won with the 80.28% of the votes.

Table 1, that shows the results of the presidential and parliamentary elections in Tanzania from 2005 to 2020, we observe that the vote share of CCM in National elections slowly decreases in the first decade of the XXI century. The 2015 national elections, which we considered in our research, were the most "democratic" in Tanzanian political history. The share of votes of CCM hit its lowest point with a total of 58.5% of votes, a huge drop from the 80.3% of 2005.

Table 1: Tanzanian National Election Results from 2005 to 2020

Election	Party	Presidential	Parliamentary
2005	CCM	80.3%	88.8%
	Opposition	19.7%	11.2%
2010	CCM	62.8%	77.8%
	Opposition	37.2%	22.2%
2015	CCM	58.5%	73.4%
	Opposition	41.5%	26.6%
2020	CCM	84.4%	97.0%
	Opposition	15.6%	3.0%

Notes: Opposition percentage considered as aggregate of all the opposition parties' shares
Source: Paget (2021)

When President Magufuli was elected in November 2015, he devised a strategy for suppressing opposition parties based on his authority, which he heavily emphasized throughout his five-year term. Through repression and freedom-limiting policies, Magufuli slowly established a CCM hegemony, as evidenced by the 2020 election results, when he won the elections with an astounding 84% of the total votes cast, the highest ever recorded since multipartyism was introduced, reversing years of opposition achievement at the national and ward-levels. (Collord 2021).

3.2. Education development plans

Over the last two decades, CCM governments have implemented a number of policies to improve Tanzania's academic sector, which was previously characterized by low teaching quality and low enrollment rates, particularly in rural areas. One of the most significant achievements of the past twenty years has been the execution of two key programs, the PEDP and the FSE. In 2002, the Tanzanian government approved indeed the *Primary Education Development Plan* (PEDP), which aimed to increase schooling capacity and significantly improve primary education quality (Davèn 2008). As the main goal of the PEDP program, the Tanzanian Government made completely free primary education, abolishing tuition and exam fees for all families across the country. As a consequence, the Gross Enrolment Ratio increased by almost 20% from 2000 to 2002 (Shukia 2020).

After 13 years, in 2015, Tanzania abolished fees also for state-run secondary schools, becoming one of the first low-income countries to guarantee eleven years of free-schooling. President Magufuli strongly encouraged the free education system, allocating a fund of 18 billion of TZS (around 5.7 million GBP) to implement the new directives (Right to Education 2016).

3.3. The PSLE test

Tanzanian education consists of two years of pre-primary school, seven years of primary school and six years of secondary school, divided in turn in four years of secondary and two years of advanced secondary education. By the end of the primary school, in September, seventh grade students must take the *Primary School Leaving Examination* (PSLE) test, required to access secondary education. The PSLE test is divided in five sub-sections: English, Kiswahili, Mathematics, Science and Social Studies. Students can achieve a maximum of 50 points per sub-sections, expressed with letter grades: A corresponds to a score between 50 and 40, B between 39 and 30, C between 29 and 20, D between 19 and 10 and E between 9 and 0. Each student needs at least 100 points in total to pass the exam. In 2021, the 82% of pupils passed the examination (Mhagama 2021). When compared to data from 2021, the number of candidates registered for the 2022 PSLE exams increased by more than 20%.

4. Data description

To conduct this study, we draw on the universe of election outcome and standardized-test scores in Tanzania. The final dataset used for the analysis is the result of the merge between two sub-datasets. The first dataset contains data regarding ward-level election results in 2015. For each of the traceable 2942 Tanzanian wards, we have information on parties that run for the elections, the name of the candidates, the total number and the share of votes for each party. Using this data, it was possible to create the dummy variables *win_CCM*, *win_CHADEMA* and *win_CUF*, equal to one if that specific party won the elections in the ward. Table 2 provides a summary of the main variables from the first dataset used for this research:

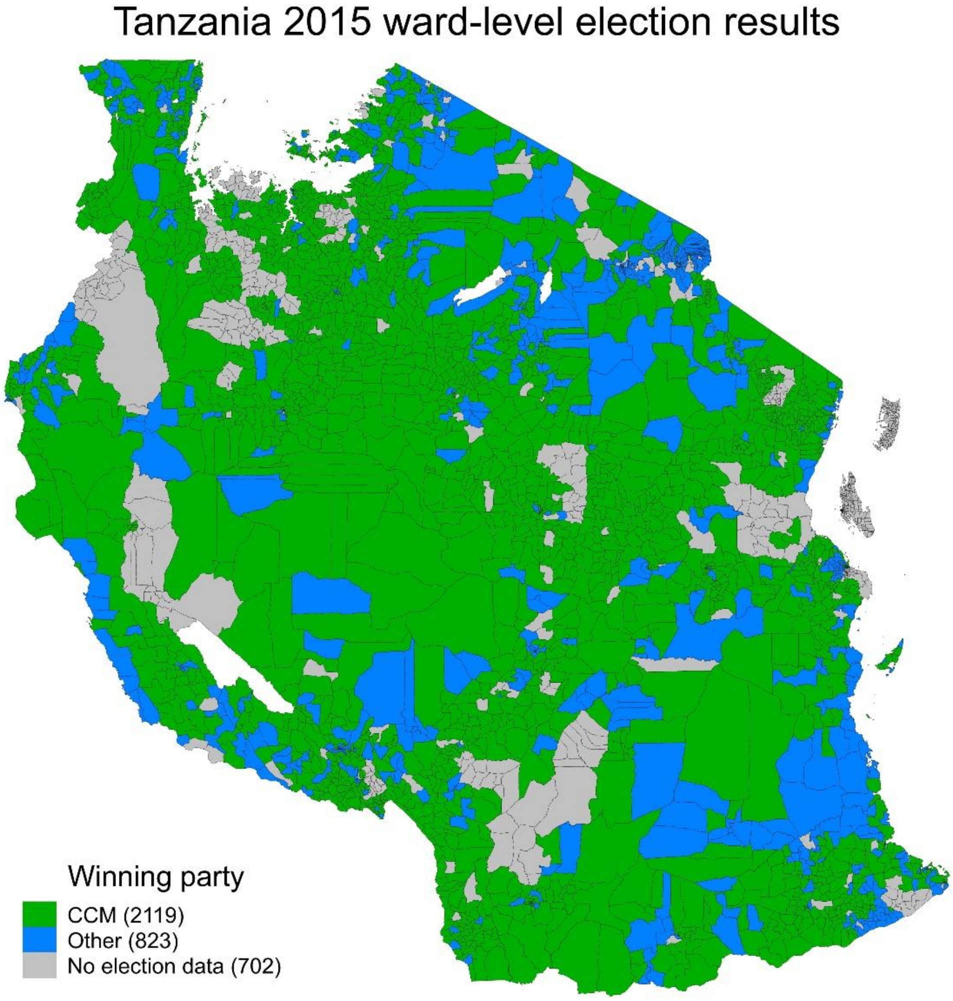
Table 2: Summary statistics: election results

Variables	**Description**	**Mean**	**Standard deviation**	**min**	**max**
num_votesCCM	total number of votes for CCM candidate in each ward	2643.585	1959.955	0	13612
num_votesCHADEMA	total number of votes for the CHADEMA candidate in each ward	2321.452	2526.564	0	15527
num_votesCUF	total number of votes for the CUF candidate in each ward	1016.674	1897.36	1	14294
party_win	name of the party that won the elections in each ward	/	/	/	/
share_win	share of voter support of the candidate who won the elections in each ward	0.604	0.114	0.313	1
party_runnerup	name of the runner-up party in each ward	/	/	/	/
share_runnerup	share of voter support of the runner-up party candidate in each ward	0.355	0.105	0	0.499
total_votes	total number of votes in each ward	5211.816	4526.471	0	29202

num_cands	number of candidates in each ward	2.969	1.193	1	11
margin	difference between the share of votes of the party that won the elections and the share of votes of the runner-up party	0.249	0.209	0.001	1
win_CHADEMA	dummy variable equal to 1 if CHADEMA won the ward-level elections in each ward	0.265	0.441	0	1
win_CCM	dummy variable equal to 1 if CCM won the ward-level elections in each ward	0.677	0.467	0	1
win_CUF	dummy variable equal to 1 if CUF won the ward-level elections in each ward	0.038	0.191	0	1

Figure 1 displays all the mappable Tanzanian ward-level election results for the whole country. We can see the prevailing proportion of wards in which CCM won the elections, in particular in the central areas. Other parties won the elections mainly in the north and south-east region of the country.

Figure 1: Map of ward-level election results in Tanzania, 2015



CCM won 730 unmappable ward elections. Other parties won 231.

The second dataset is based on *National Examinations Council of Tanzania* (NECTA) information regarding PSLE test scores of students in Tanzania in the period 2013-2019. Each student is associated with a school located in a specific ward. The dataset contains information regarding the marks and the characteristics of the students and the characteristics of the schools. Table 3 provides a summary of the main variables from the second dataset used for the study:

Table 3: Summary statistics: PSLE results and school characteristics

Variables	**Description**	**Mean**	**Standard deviation**	**min**	**max**
year	year of the test	/	/	2013	2019
marks_overall	sum of midpoint of range of subject-specific marks, divided by the number of subjects	46.646	17.207	0	90
female	dummy variable that indicates whether a student is a girl or a boy	0.528	0.499	0	1
gov	dummy variable that indicates whether the school is run by the Government	0.967	0.179	0	1

In both datasets, we created the variables *gadm_reg_id*, *gadm_dist_id* and *gadm_ward_id* that uniquely identify the region, district and ward of the candidate or the school. On the basis of these common variables, it was possible to merge the two datasets.[5]

5. Methodology

In the following subsection we are going to present the main model we have employed, the Sharp Regression Discontinuity (Sharp RD) design. In the RD design, each unit is given a score, and we assign a treatment status only to the observations for which the score is higher than a determined cut-off (or threshold), while the units that have a score below the cut-off are assigned to the so-called control condition (Cattaneo, Idrobo and Titiunik 2019). When implementing this methodology, we presume that the probability of receiving the treatment will change discontinuously at the threshold with some observable continuous variable X_i. We can write the treatment model with heterogeneous effects:

$$Y_i = \beta_i + \tau_i T_i + e_i$$
$$e_i = (\beta_i - \beta) + T_i(\tau_i - \tau).$$

[5] Using the *merge* command on STATA we obtain three possible levels of merge: $\_m = 1$ and $\_m = 2$ correspond to observations that are included only in one of the two datasets, respectively. We focus on the observations for which $\_m = 3$, indeed included in both datasets.

The first underlying assumption of the RD design states that the treatment variable T_i is a function of the assignment variable X_i discontinuous at the cut-off point c:

$$\lim_{x \to c^-} P(T_i = 1|X_i = x) \neq \lim_{x \to c^+} P(T_i = 1|X_i = x)$$

with $E[\beta_i|X_i = x]$ and $E[\tau_i|X_i = x]$ continuous at $x = c$ and τ_i independent from T_i in the neighborhood of c.

In order to identify the average treatment effect, we must rely on the smoothness assumption:

$$E[Y_0|X_i = x] \text{ and } E[Y_1|X_i = x] \text{ are continuous in } x = c$$

where Y_0 and Y_1 represent the potential outcomes under the control or the treatment condition (Lee 2008).[6]

When the unit has $X_i \geq c$, we say that the unit is assigned to the treatment condition. In a Sharp Regression Discontinuity design, being assigned to the treatment condition corresponds to receive the treatment, and the probability of receiving the treatment:

$$p(x) \equiv P(T_i = 1|X_i = x)$$

changes from zero to one at the cut-off. The observed outcome is:

$$Y_i = (1 - T_i) \cdot Y_i(0) + T_i \cdot Y_i(1) = \begin{cases} Y_i(0)\ if\ X_i < c \\ Y_i(1)\ if\ X_i \geq c \end{cases}$$

Given the average potential outcomes $E[Y_i(1)|X_i = x]$ and $E[Y_i(0)|X_i = x]$,[7] in a Sharp RD design we can write the observed average outcome as:

$$E[Y_i|X_i] = \begin{cases} E[Y_i(0)|X_i]\ if\ X_i < c \\ E[Y_i(1)|X_i]\ if\ X_i \geq c \end{cases}$$

[6] Lee (2008) shows two empirical limitations to the assumption. Firstly, the assumption only explains mathematically what is needed to identify a causal effect, but practically it does not refer to a treatment-assigning process. Secondly, it is usually almost impossible to verify the reasonability of the assumption in a real-world context.

[7] The regression function $E[Y_i(1)|X_i]$ is observed when $x > c$, and $E[Y_i(1)|X_i]$ is not observed when $x < c$. Indeed, when $X_i > c$, $Y_i = Y_i(1)$ for all i. We can apply the same reasoning with $E[Y_i(0)|X_i]$, with opposite considerations.

and the estimation of the average treatment effect $E[Y_1|X_i = x] - E[Y_0|X_i = x]$ at the cut-off becomes[8]:

$$\tau_i \equiv E[Y_i(1)|X_i = c] - E[Y_i(0)|X_i = c]$$

$$\tau_i \equiv E[Y_i(1) - Y_i(0)|X_i = c].$$

Since the Sharp RD design implies that all units with assignment variable equal to c are treated, τ_i can be interpreted as a local average treatment effect on the treated (Cattaneo et al., 2019). We can rewrite the smoothness assumption as:

$$E[Y_i(1)|X_i = x] \text{ and } E[Y_i(0)|X_i = x] \text{ are continuous in } x = c$$

to write the difference in limit at the cut-off:

$$E[Y_i(1) - Y_i(0)|X_i = c] = \lim_{x \to c^+} E[Y_i|X_i = x] - \lim_{x \to c^-} E[Y_i|X_i = x].$$

This equation explains that if the average potential outcomes are continuous functions at the cut-off, the average treatment effect at the cut-off can be estimated as the difference in limits of the treated and control average observed outcomes.

Retrieving the treatment model with heterogeneous effects, we can compute the local average treatment effect as:

$$\begin{aligned} E[Y_i|X_i = c] &= E[\beta_i|X_i = c] + p(x = c) \cdot E[\tau_i|T_i = 1, X_i = c] \\ &= E[\beta_i|X_i = c] + p(x = c) \cdot E[\tau_i|\, X_i = c] \end{aligned}$$

where $E[\tau_i|\, X_i = c]$ is the local average treatment effect.

The difference in limit around the cut-off is then computed as:

$$\lim_{x \to c^+} E[Y_i|X_i = x] - \lim_{x \to c^-} E[Y_i|X_i = x] = E[\tau_i|\, X_i = c]\left[\lim_{x \to c^+} p(x) - \lim_{x \to c^-} p(x)\right]$$

and we can write:

[8] As in Cattaneo et al. (2019), we cannot observe both $E[Y_i(1)|X_i = x]$ and $E[Y_i(0)|X_i = x]$ since the control and the treatment group cannot have the same value of the assignment variable. In their estimation, they compare units with score equal to the cut-off and units with score barely below the cut-off, that differ only for their treatment status.

$$E[\tau_i|\, X_i = c] = \frac{\lim_{x\to c^+} E[Y_i|X_i = x] - \lim_{x\to c^-} E[Y_i|X_i = x]}{\left[\lim_{x\to c^+} p(x) - \lim_{x\to c^-} p(x)\right]}$$

Since in a Sharp RD design $p(x)$ is either zero or one in different sides of the cut-off, the denominator of the above equations is equal to one and we can write the local average treatment effect as:

$$E[\tau_i|\, X_i = c] = \lim_{x\to c^+} E[Y_i|X_i = x] - \lim_{x\to c^-} E[Y_i|X_i = x]$$

5.1. Sample clustering

As in Abadie et al. (2022), clustering our sample at ward-level becomes extremely relevant in the study for two main reasons. The first reason is that in our research we observe the entire population of interest, and we cannot exclude *ex ante* that some observations within clusters are not related to each other for observable and unobservable individual attributes, such as ability or socioeconomic background. The second and most relevant reason is that the units assigned to the treatment of political control are indeed the wards (i.e., clusters of individuals). Since the treatment is not assigned at individual level, we must adjust our estimates clustering by wards (McKenzie 2017).[9]

[9] See Abadie et al. (2017), paragraph 3.3, 3.4 and Appendix for the computation of the least squares estimator for τ_i in case of clustering.

6. Results

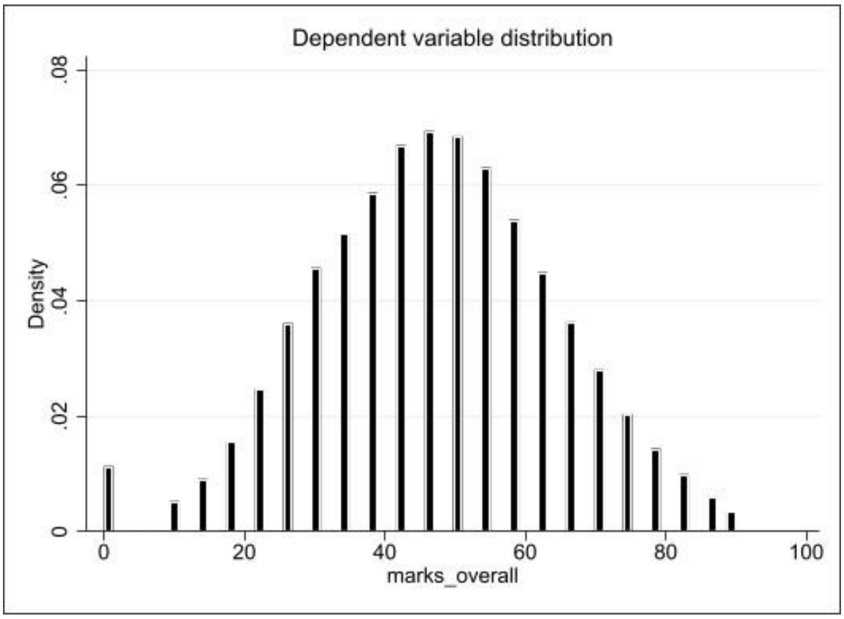
In the study we focus on understanding the impact of the ward-level elections on the academic results in school. The dataset includes test scores from 2013 to 2019, and we take into consideration the test scores from 2016 and 2019, since test results before 2016 are not affected by the elections outcome.[10] The model employed for the main part of the study is the Regression Discontinuity design. As in many RD design, we want to determine the effect that the binary treatment variable T_i has on the outcome Y_i (Hahn et al. 2001).

We investigate the variation of the impact of the elections on the test scores through the years, comparing the scores in 2016 to the results in 2017, 2018 and 2019. Retrieving our research question, we want to analyze the effect that the treatment status, the political control of CCM in a ward, expressed by the binary variable *win_CCM*, has on school performances of students. We employ as dependent variable the variable *marks_overall*, defined as the average score obtained by a single student in the PSLE test score. We choose this variable as measure of student achievement, a widely used indicator for education service quality. The variable is computed adding the midpoint of range of each subject-specific mark and dividing the total sum by 5.[11] In Figure 2 below we can see the distribution of the dependent variable.

[10] The elections happened between October and November 2015, while the PSLE test is taken every year in September. Therefore, school performances before 2015 elections (i.e., 2013, 2014 and 2015 test results) are not affected by the treatment variable.

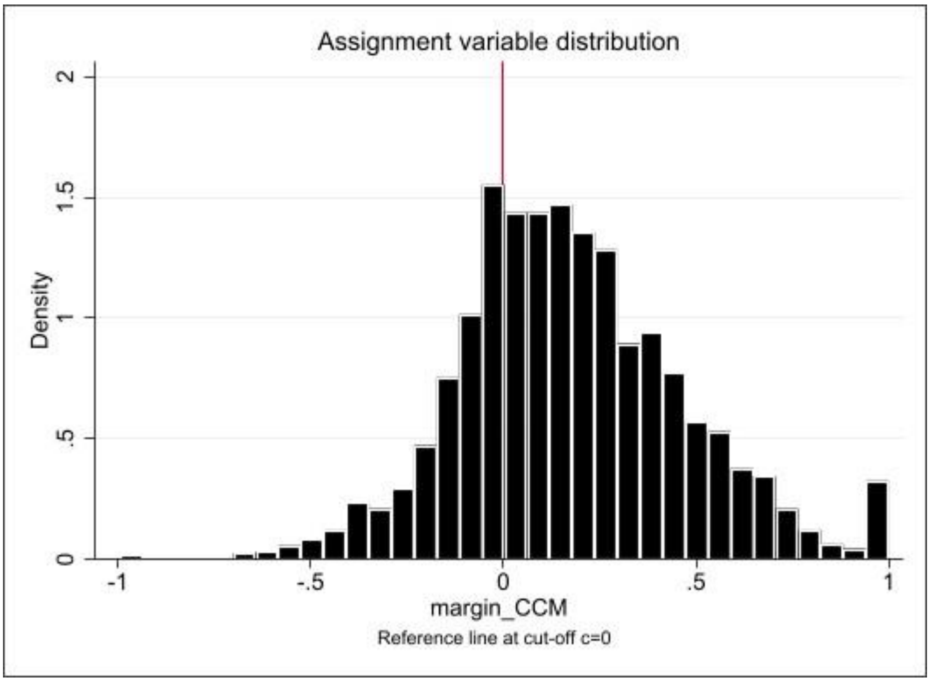
[11] As in Sandholtz (2022), each subject-specific score of the PSLE exam is converted to a 100-point scale before computing the variable *marks_overall*.

Figure 2: Dependent variable distribution



The presence of a mass in zero is due to the number of students who did not finish the test or did not attend the exam, resulting in a grade of zero. In our model, the assignment variable *margin_CCM* is computed from the variable *margin*, that represents the difference between the share of votes of the party that won the elections in the ward (*share*_win) and and the share of the runner-up party (*share_runnerup*). In particular, the variable *margin_CCM* assumes value equal to the values of *margin* in case CCM won the elections, and value equal to the difference between the share of the winner and the share of CCM (*share_CCM*) if the opposition won. Figure 3 displays the distribution of the assignment variable, relative to the cut-off.

Figure 3: Assignment variable distribution

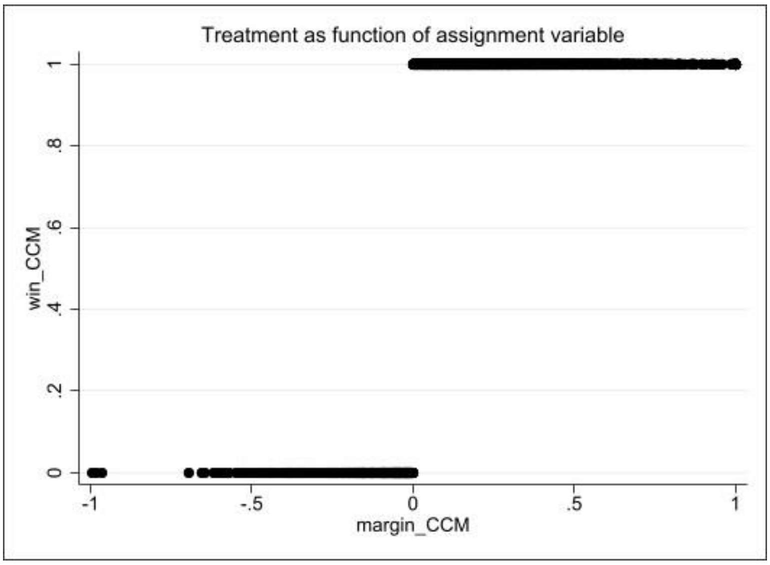


We observe that the distribution does not present peaks and it is almost smooth. Hence, we can exclude a non-random variation at the cut-off, that could be associated to a possible manipulation of votes. The masses at 1 and -1 are due to the fact that some wards in our study only had one candidate, and thus CCM or the opposition candidate won the elections with 100% of the votes[12].

As previously discussed, in a Sharp RD design the probability of receiving a treatment jumps from zero to one at the cutoff. Figure 4 shows the relationship between the treatment variable T_i of our research, *win_CCM*, and the assignment variable X_i, *margin_CCM*:

[12]In presence of only one candidate, $margin\_CCM = share\_win - share\_runnerup = \pm 1$.

Figure 4: Treatment as function of assignment variable



Looking at the plot, we can observe that the treatment is fully determined by the forcing variable:

$$T_i = 1 \ if \ X_i \geq 0, \text{ with } c = 0.$$

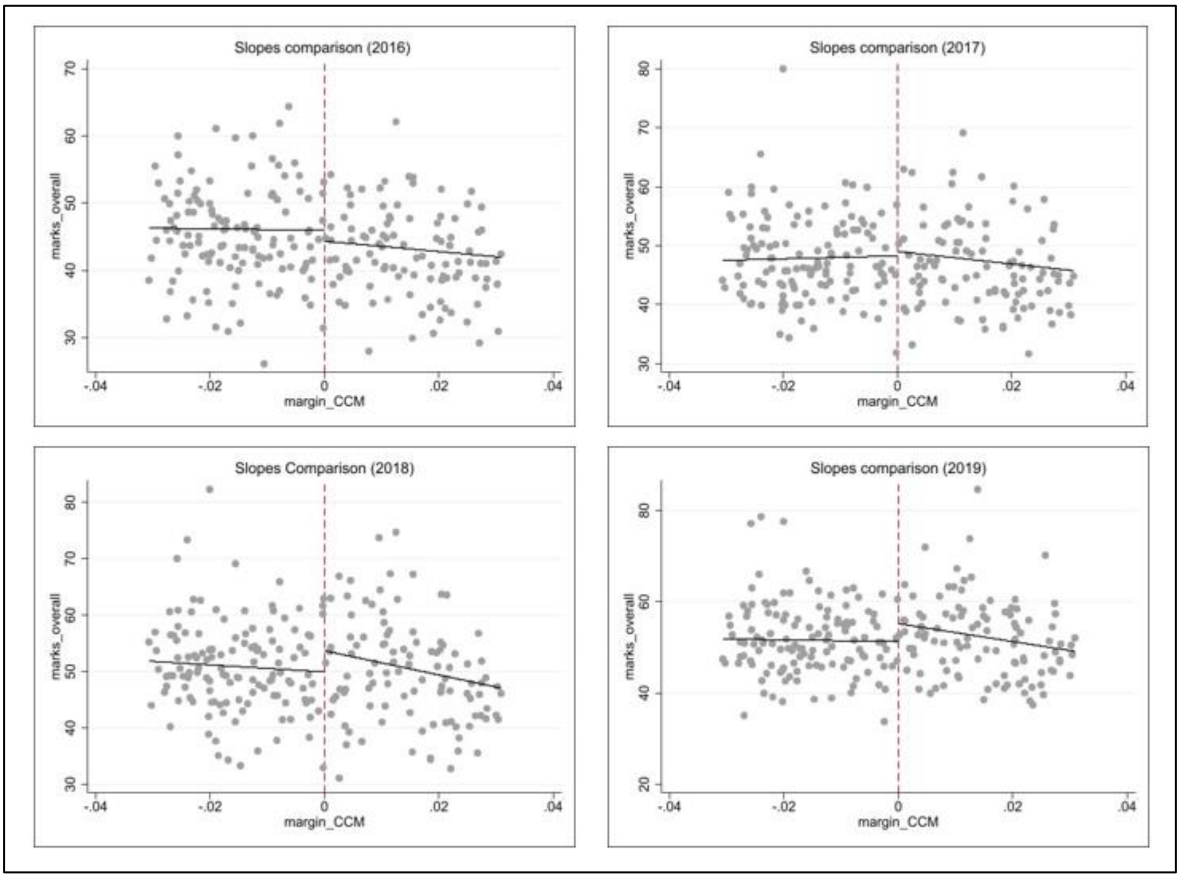
In this case, a Sharp Regression Discontinuity approach seems to be appropriate. Since we expect the probability of receiving the treatment changing discontinuously at the cut-off, we expect that the average grade of the test changes when the value of *margin_CCM* is close to the cut-off value. Following the computation proposed by Cattaneo, Titiunik and Vazquez-Bare (2020), we adopt in our research the optimal bandwidth that minimizes the mean squared error (MSE) of the RD treatment effect, that considers values at right and left to the cut-off equal to ± 0.031.[13]

Figure 5 shows the relationship between our outcome variable *marks_overall* and the assignment variable *margin_CCM* of observations from 2016 to 2019 around the cut-off, considering the individuals in the mentioned bandwidth. Observing the different regression

[13] The optimal bandwidth has been computed on STATA with the command *rdbwselect*, that is part of the *rdrobust* package suggested by Cattaneo, Titiunik and Vazquez-Bare (2020). For the empirical computation see Cattaneo, Titiunik and Vazquez-Bare (2020) and Imbens and Kalyanaraman (2012).

lines at the left and right of the threshold, we can notice the discontinuity in correspondence of the cut-off point.

Figure 5: Assignment and dependent variable relationship



To analyze the variation of the coefficient of our treatment variable from 2016 to 2019, we employ different types of regression on our dependent variable *marks_overall*. As mentioned in the previous section, we necessarily cluster our sample at ward-level, and therefore we use cluster standard errors in each specification. To estimate the causal effect of the treatment, we start implementing the original linear regression that includes only the treatment variable *win_CCM* and the forcing variable *margin_CCM*:

$$marks_{overall} = \beta + \tau win_{CCM} + \delta_1 margin_{CCM} + \varepsilon_i.$$

The estimates of the regression are displayed in Column 1 of Table 4. Although the coefficient increases over the years, with only negative impacts in 2016, the relationship between the treatment variable and the dependent variable is statistically insignificant at 10% significance level for each year.

Column 2 to Column 4 present the estimates of the original specification with the addition of some control variables (Column 2), the interaction term between the forcing and the treatment variable (Column 3) and both controls and interaction term (Column 4). In particular, the interaction term, computed as $win_{CCM} \times margin_{CCM}$, is usually necessary in designs in which the slopes for treated and control units differs for the so-called interaction effect.[14] Figure 5 shows that the regression lines around the cut-off run almost parallel in 2016 and 2017, but have slopes slightly different in 2018 and 2019. In this case, omitting the interaction term could result in an inaccuracy in the estimation of the effect of the treatment on the outcome. Moreover, we can use the regression with the controls and the interaction term as robustness check of our model. We choose to control for the students' gender (*female*) and the type of school (*gov*), to have a control based on both students and school characteristics[15].

Column 4 displays the result of the following regression:

$$marks_{overall} = \beta + \tau win_{CCM} + \delta_1 margin_{CCM} + \delta_2 margin_{CCM} \times win_{CCM} + \gamma_1 female + \gamma_2 gov + \varepsilon_i.$$

Comparing the four columns, we observe that the values of estimates and standard errors remain almost constant across the specifications. We do not see any significant change in the coefficients of the treatment variable, that keeps the same sign and similar magnitude over the years in each column. In particular, from Column 1 to Column 2 we notice only an increase in the R-squared of the models and a reduction of the standard errors associated to the treatment. Including the interaction term, on the other hand, considerably increases the magnitude of the treatment effect, as shown in Column 3. Still, the effect of our treatment on the election

[14] When slopes are the same, we can ideally identify the treatment effect around the cut-off by calculating the difference of the intercepts of the regression lines around the threshold.
[15] The choice of *gov* as control for school characteristics relies on the fact that secondary school fees were abolished for state-run schools.

outcomes is not statistically significant at 10% significance level for almost every specification. Although the results in Column 4 are very similar with results in Column 1 to 3, we observe that the coefficient of *win_CCM* in 2019 is significant at 10% significance level. In particular, test scores of students in wards ruled by the CCM are 3.77 points higher on average than students in wards under control condition.

Table 4: Regression on marks_overall: results

year	variable	*Column 1* **No controls**	*Column 2* **With controls**	*Column 3* **With interaction term**	*Column 4* **With controls and interaction term**
2016	win_CCM	-1.76	-1.94	-1.62	-1.84
		(2.14)	(1.88)	(2.17)	(1.91)
	margin_CCM	-36.79	-22.22	-10.93	-3.52
		(64.44)	(58.24)	(88.92)	(78.38)
N		63,908	63,908	63,908	63,908
R-squared		0.009	0.102	0.010	0.103
2017	win_CCM	0.41	0.54	0.73	0.38
		(2.32)	(1.99)	(2.31)	(1.96)
	margin_CCM	-25.46	-8.11	25.14	42.76
		(74.29)	(63.62)	(105.08)	(87.66)
N		70,363	70,363	70,363	70,363
R-squared		0.000	0.079	0.002	0.080
2018	win_CCM	3.37	3.01	3.75	3.38
		(2.76)	(2.36)	(2.79)	(2.39)
	margin_CCM	-122.52	-101.52	-62.26	-43.48
		(80.42)	(66.91)	(111.84)	(88.91)
N		71,889	71,889	71,889	71,889
R-squared		0.004	0.079	0.005	0.081
2019	win_CCM	3.42	3.26	3.93	3.77*
		(2.57)	(2.32)	(2.55)	(2.21)
	margin_CCM	-86.07	-68.08	-18.92	-1.37
		(75.16)	(62.29)	(106.07)	(84.26)
N		70,783	70,783	70,783	70,783
R-squared		0.025	0.089	0.004	0.092

Notes: Standard Errors clustered at the municipality level reported in parentheses for the coefficient of interest.
$* p < 0.1$, $** p < 0.05$, $*** p < 0.01$
The optimal bandwidth restricts the wards' sample at 261 wards, almost the 10% of the total number.

6.1. Falsification test

To test the reliability of our model, we perform a simple placebo test following the idea in Rothstein (2010). We expect that pupils' performances are not affected by elections not yet happened, and therefore that the treatment assignment does not influence their scores. We implement the same specifications as in Table 4 on test scores focusing on years prior to 2015 elections. The results are summarized in Table 5:

Table 5: Falsification test: Regression on marks_overall from 2013 to 2015

year	variable	*Column 1* **No controls**	*Column 2* **With controls**	*Column 3* **With interaction term**	*Column 4* **With controls and interaction term**
2013	win_CCM	-2.01 (1.91)	-1.76 (1.73)	-2.07 (1.91)	-1.84 (1.72)
	margin_CCM	7.57 (57.29)	9.59 (54.19)	-6.95 (70.44)	13.80 (65.38)
N		67,875	67,875	67,875	67,875
R-squared		0.003	0.050	0.003	0.051
2014	win_CCM	-0.77 (2.19)	-0.68 (1.99)	-0.52 (2.25)	-0.47 (2.04)
	margin_CCM	7.59 (69.15)	12.33 (63.83)	56.74 (90.24)	51.92 (80.93)
N		65,303	65,303	65,303	65,303
R-squared		0.000	0.063	0.002	0.064
2015	win_CCM	-1.14 (2.46)	-1.22 (2.23)	-0.85 (2.44)	-0.97 (2.23)
	margin_CCM	25.16 (78.73)	35.39 (71.19)	72.68 (110.17)	75.36 (97.04)
N		63,115	63,115	63,115	63,115
R-squared		0.000	0.060	0.001	0.061

Notes: Standard Errors clustered at the municipality level reported in parentheses for the coefficient of interest.
* $p < 0.1$, ** $p < 0.05$, ***$p < 0.01$
The optimal bandwidth restricts the wards' sample at 261 wards, almost the 10% of the total number.

The treatment variable estimates from 2013 to 2015 are statistically not significant for each specification implemented. As expected, 2015 elections do not have any causal impact on PSLE outcomes for previous years.

7. Concluding remarks

The objective of this study is to investigate whether students in wards aligned with the ruling party achieve better school performances than students in wards ruled by the opposition, in order to determine whether the effects of free education programs in Tanzanian wards are affected by politics. Drawing on the universe of standardized test scores and ward-level election results in Tanzania, we implemented a Sharp Regression Discontinuity design to analyze the impact that CCM's election victory has on PSLE scores from 2016 to 2019. Regardless the specification chosen, we failed to find any significant increase in pupils' test scores in areas aligned with the government compared to areas ruled by the opposition. Recalling Abdulai and Hickey (2016), we hypothesized that the government may have addressed differently the benefits of the programs on the basis of the party of the local government. However, we found no significant effect that the CCM victory leads to higher average test scores. We obtained a significant result only using the specification that includes both controls and interaction term, with data from 2019. In this case, the treatment seems to have a positive effect on the grades, and students seem to achieve better results in wards politically aligned with CCM.

Although the difference in scores is not significant enough to conclude that the free education programs impacted differently within the country, future research could focus on the variation in coefficient in Table 4 across years compared to the variation in CCM vote share between 2015 and 2020 displayed in Table 1. In our theoretical considerations, we highlighted indeed Magufuli's autocratic behavior, which resulted in a substantial boost in vote share comparing 2015 to 2020 elections. Similarly, our estimates rise over time, peaking in 2019, when the average score is 3.77 points higher in treated wards, in light of the significant estimate in Table 4. Accordingly, we may assume that schooling outcomes are somehow influenced by the presence of the ruling party, that may have an impact on other education provision factors, such as the preparation of teachers or the quality of school facilities. Further research on allocation of education expenditures across the country is required to validate this assumption and ensure that education funding is effectively distributed evenly in Tanzania.

A major limitation to our study is related to the impossibility to identify the election outcome for each Tanzanian ward. The process of identification was constrained by the absence of information regarding 702 wards across the country, as shown in Figure 1. As a consequence, we are unable to extend the study to the entire country, even if we can confirm that a large portion of wards has been considered in the research. Another limitation to our study is the absence of information regarding the turnover in ward-level elections before and after 2015. Hence, we cannot compare the outcomes in wards where the ruling party changed after 2015 elections, and we cannot investigate how the change in alignment affects test scores in our sample, as it is tested in Akhtari, Moreira and Trucco (2022).

This work project opens scope for further research to investigate the influence of the Tanzanian ruling party on resource allocation, with specific outlook on education. Retrieving Paget (2021), CCM is persevering in constricting political space and social freedom, and its autocratic behavior may conduct to more evident inequalities in the next future. Further analysis is needed to ensure that the free education programs are implemented uniformly across the country, considering also the shocking results of 2020 elections. As a final suggestion, investigating the impact of ward-level election turnover in 2015 on education outcomes in the years following the elections could be useful to analyze the influence of CCM on local politics, with a focus on the schooling sector.

Bibliography

Abadie, Alberto, Susan Athey, Guido W. Imbens, and Jeffrey Wooldridge. 2017. "When Should You Adjust Standard Errors for Clustering?" National Bureau of Economic Research. November 1, 2017. https://www.nber.org/papers/w24003.

Abadie, Alberto, Susan Athey, Guido W Imbens, Jeffrey M Wooldridge, When Should You Adjust Standard Errors for Clustering?, *The Quarterly Journal of Economics*, 2022;, qjac038, https://doi.org/10.1093/qje/qjac038

Abdulai, Abdul-Gafaru, and Sam Hickey. 2016. "The Politics of Development under Competitive Clientelism: Insights from Ghana's Education Sector." *African Affairs* 115/458 (44-72): adv071. https://doi.org/10.1093/afraf/adv071.

Akhtari, Mitra, Diana Moreira, and Laura Trucco. 2022. "Political Turnover, Bureaucratic Turnover, and the Quality of Public Services." *American Economic Review* 112 (2): 442–93. https://doi.org/10.1257/aer.20171867.

Ansolabehere, Stephen, and James M. Snyder. 2006. "Party Control of State Government and the Distribution of Public Expenditures." *The Scandinavian Journal of Economics* 108 (4): 547–69. https://www.jstor.org/stable/4121593.

Brollo, Fernanda, and Tommaso Nannicini. "Tying Your Enemy's Hands in Close Races: The Politics of Federal Transfers in Brazil." *The American Political Science Review* 106, no. 4 (2012): 742–61. http://www.jstor.org/stable/23357707.

Cattaneo, Matias D., Nicolás Idrobo, and Rocío Titiunik. *A Practical Introduction to Regression Discontinuity Designs: Foundations*. Elements in Quantitative and Computational Methods for the Social Sciences. Cambridge: Cambridge University Press, 2020. doi:10.1017/9781108684606.

Cattaneo, Matias D., Rocío Titiunik, and Gonzalo Vazquez-Bare. 2020. "The Regression Discontinuity Design." *The SAGE Handbook of Research Methods in Political Science and International Relations*, 835–57. https://doi.org/10.4135/9781526486387.n47.

Collord, Michaela. 2021. "Tanzania's 2020 Election Return of the One-Party State." *Études de L'Ifri*. https://www.ifri.org/sites/default/files/atoms/files/collord_tanzania_2020_election_2021.pdf.

Davén, Jonatan. "Free Primary Education in Tanzania? : A case study on costs and accessibility of primary education in Babati town." (2008).

Hahn, Jinyong, Petra Todd, and Wilbert Van der Klaauw. 2001. "Identification and Estimation of Treatment Effects with a Regression-Discontinuity Design." *Econometrica* 69 (1): 201–9. https://www.jstor.org/stable/pdf/2692190.pdf?refreqid=excelsior%3A0ef1d0f507977386772fa0e3b8e1f4da&ab_segments=&origin=&acceptTC=1.

Hyytinen, Ari, Jaakko Meriläinen, Tuukka Saarimaa, Otto Toivanen, and Janne Tukiainen. 2018. "When Does Regression Discontinuity Design Work? Evidence from Random Election Outcomes." *Quantitative Economics* 9 (2): 1019–51. https://doi.org/10.3982/qe864.

Imbens, Guido, and Karthik Kalyanaraman. 2011. "Optimal Bandwidth Choice for the Regression Discontinuity Estimator." *The Review of Economic Studies* 79 (3): 933–59. https://doi.org/10.1093/restud/rdr043.

Imbens, Guido W., and Thomas Lemieux. 2008. "Regression Discontinuity Designs: A Guide to Practice." *Journal of Econometrics* 142 (2): 615–35. https://doi.org/10.1016/j.jeconom.2007.05.001.

Jensenius, Francesca R., and Pradeep Chhibber. 2022. "Privileging One's Own? Voting Patterns and Politicized Spending in India." *Comparative Political Studies*, August, 001041402211094. https://doi.org/10.1177/00104140221109430.

Knutsen, Carl Henrik, Autocracy and Variation in Economic Development Outcomes (November 2018). V-Dem Working Paper 2018:80, Available at SSRN: https://ssrn.com/abstract=3286949 or http://dx.doi.org/10.2139/ssrn.3286949

Lee, David S. 2001. "The Electoral Advantage to Incumbency and Voters' Valuation of Politicians' Experience: A Regression Discontinuity Analysis of Elections to the U.S..." *National Bureau of Economic Research* 8441 (August). https://doi.org/10.3386/w8441.

Lee, David S. 2008. "Randomized Experiments from Non-Random Selection in U.S. House Elections." *Journal of Econometrics* 142 (2): 675–97. https://doi.org/doi.org/10.1016/j.jeconom.2007.05.004.

Macdonald, Bobbie, Incumbency Disadvantages in African Politics? Regression Discontinuity Evidence from Zambian Elections (January 2014). Available at SSRN: https://ssrn.com/abstract=2325674 or http://dx.doi.org/10.2139/ssrn.2325674

McKenzie, David. 2017. "When Should You Cluster Standard Errors? New Wisdom from the Econometrics Oracle." *Development Impact* (blog). October 16, 2017. https://blogs.worldbank.org/impactevaluations/when-should-you-cluster-standard-errors-new-wisdom-econometrics-oracle.

Mhagama, Hilda. 2021. "Tanzania: How Pupils Performed in 2021 Standard Seven Exams." AllAfrica.com. November 1, 2021. https://allafrica.com/stories/202111010146.html.

Nyang'oro, Julius. 2006. "The 2005 General Elections in Tanzania: Implications for Peace and Security in Southern Africa." *ISS Paper* 122 (February). https://issafrica.org/research/papers/the-2005-general-elections-in-tanzania-implications-for-peace-and-security-in-southern-africa.

Paget, Dan. “Tanzania: The Authoritarian Landslide”. *Journal of Democracy* 32, no. 2 (April 2021): 61–76.

Rothstein, Jesse. 2010. “Teacher Quality in Educational Production: Tracking, Decay, and Student Achievement*.” *Quarterly Journal of Economics* 125 (1): 175–214. https://doi.org/10.1162/qjec.2010.125.1.175.

Sandholtz, Wayne Aaron. " Secondary school access raises primary school achievement inTanzania." (2022).

Shukia, Richard. 2020. “Fee-Free Basic Education Policy Implementation in Tanzania: A ‘Phenomenon’ Worth Rethinking.” *Huria: Journal of the Open University of Tanzania* 27 (1). https://www.ajol.info/index.php/huria/article/view/204346.

Stasavage, David. 2005. “Democracy and Education Spending in Africa.” *American Journal of Political Science* 49 (2): 343. https://doi.org/10.2307/3647681.

Treichel, Volker. 2005. “Tanzania’s Growth Process and Success in Reducing Poverty.” *SSRN Electronic Journal* 2005 (035). https://doi.org/10.2139/ssrn.874257.

Tsubura, Machiko. 2015. “Does Clientelism Help Tanzanian MPs Establish Long-Term Electoral Support?” Afrobarometer. https://www.afrobarometer.org/wp-content/uploads/2022/02/afropaperno159-clientelism-in-tanzania.pdf.

“Tanzania Implements Free Education Policy for Secondary Education.” 2016. Right to Education Initiative. January 28, 2016. https://www.right-to-education.org/news/tanzania-implements-free-education-policy-secondary-education.