The curious case of a replication

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This short note is a response to Vagnavalkya (2023) which argues that some of the results in Das (2023) have serious problems due to data and estimation errors. I have three main findings to report.

Density test for non-BJP ruled states

There is no McCrary density test failure in the case of non-BJP ruled states.

The p-values reported in the Medium post to make the claim that there was a discontinuous shift in BJP victory margin in non-BJP ruled states are calculated using the R command `DCdensity`. Das (2023) uses optimal bandwidth computed using the MSERD approach (Calonico, Cattaneo, and Titiunik (2014)) whereas `DCdensity` relies on the IK optimal bandwidth approach. Unfortunately, the IK optimal bandwidth can incorrectly indicate discontinuity even when it's not there leading to the rejection of null (Kuehnle, Oberfichtner, and Ostermann (2021))[1]. Using the standard R command for the density test (rddensity) as well as running `DCdensity` with half the bandwidth reported in the Medium post[2], I rule out the possibility of the failure of the McCrary test, for the non-BJP ruled states, in the 2019 Lok Sabha elections.

Growth rate of electorate in close elections

The growth rate of electorate is indeed lower in close contests where BJP won.

The original post on Medium uses the `RDestimate` command in R whose results are strikingly similar to the aggregate PC level findings reported in Das (2023). The reported estimate is -0.044 (4.4%) with a p-value of 0.01. However, one should transparently report all possible results by varying two key parameters: bandwidth (the window around the cutoff) and kernel (the assignments of weights to the observations

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[1] For detailed technical exposition on density estimators, please see Cattaneo and Vazquez-Bare (2017) and Cattaneo, Jansson, and Ma (2020)

[2] It is standard in the literature to see how sensitive results are to changes in the bandwidth.

around the cutoff). The tables below report all the results produced by `rdrobust`[3] command in R. There are two sets of results. The first set (Table 1) reports the estimates by varying the bandwidth. The results remain stable and close to the estimates provided in Das (2023). The confidence intervals of all these estimates overlap and we can argue that in close elections won by the BJP, the growth rate of electorate is 5% lower than the seats won by non-BJP parties. One might be worried that these results are driven by the choice of kernel. I run the model with the optimal bandwidth and vary the kernel; results are reported in Table 2. I show that the effect size remains stable and closer to those reported in Das (2023).

Dealing with 'outliers'

We cannot arbitrarily drop observations in the neighbourhood of the cutoff while using regression discontinuity design.

The last of the arguments in the Medium post is about handling outliers in the data. The post adopts an unusual strategy to show that the growth rate of voters between 2014 and 2019 was no different in close contests involving the BJP. The author removes some of the observations around the cutoff. Unfortunately, this is erroneous. One cannot pick and choose observations around the cutoff; RDD hinges on having all possible data points in the vicinity of the cutoff. The correct procedure to deal with the outlier problem in RDD is to run what is known as the 'donut' RDD. I perform the donut RDD by trimming the running variable at the margin of 0.5% (0.005) around the cut-off and show that the results only shift marginally. Table 3 reports these results.

To sum up, the estimates and the graphs provided in Vagnavalkya (2023) are misleading and are based on poor understanding of how regression discontinuity design works.
I wish to thank Yajnavalkya for posting the code and the dataset on Github.

[3]While `RDestimate` relies on local linear regression, `rdrobust` deploys local polynomial regressions.

Table 1: Electorate growth rate in PCs barely won by BJP (Different bandwidths)

	Bandwidth = 0.127 (MSERD)	Bandwidth = 0.106 (CER-SUM)	Bandwidth = 0.094 (CER-COMB1)
Bias-Corrected	-0.051**	-0.049**	-0.047*
	(0.017)	(0.018)	(0.019)
Robust	-0.051**	-0.049*	-0.047*
	(0.019)	(0.020)	(0.020)
Number of observations	156	129	113

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
The first column reports the bandwidth from the MSERD procedure, the second column has the bandwidth from the CER(coverage error rate)-optimal bandwidth selector for the sum of regression estimates, and the third column applies the bandwidth from the minimum of two CER-optimal bandwidth selectors. Robust standard errors in the parentheses.

Table 2: Electorate growth rate in PCs barely won by BJP (Different kernels)

	Kernel: Triangular	Kernel: Epanechnikov	Kernel: Uniform
Bias-Corrected	-0.051**	-0.052**	-0.043**
	(0.017)	(0.017)	(0.016)
Robust	-0.051**	-0.052**	-0.043*
	(0.019)	(0.019)	(0.018)
Number of observations	156	143	159

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All the estimates are based on the optimal bandwidth using the MSERD procedure (Calonico et. al. 2014). Robust standard errors are reported in the parentheses.

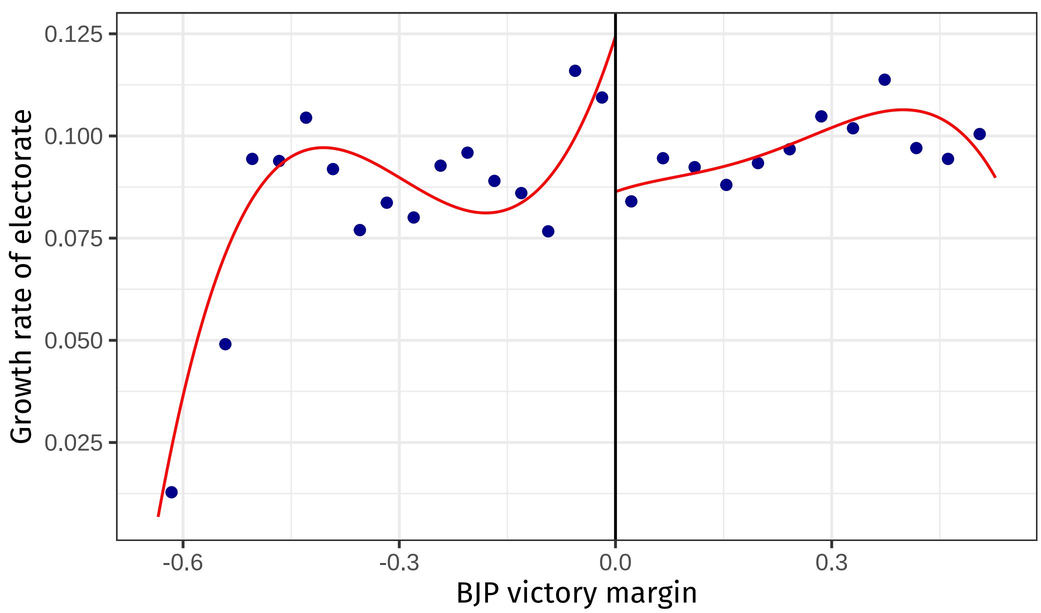

Figure 1: RD chart: Growth rate of electorate v BJP victory margin

Table 3: Donut RD estimate

Bias-Corrected	-0.042**
	(0.016)
Robust	-0.042*
	(0.019)
Number of observations	184

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001
The estimates are based on the optimal bandwidth using the MSERD procedure (Calonico et. al. 2014). Robust standard errors are reported in the parentheses.

References

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