

Examining the Effects of Close Gubernatorial Elections on Corrections Spending from 1977 to
2022 using Regression Discontinuity Design

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Abstract:

As Republicans take a more “tough on crime” stance in politics, Democrats have at times portrayed themselves as pushing back against this stance and opting for reform. Using the quasi-random nature of electoral outcomes in close gubernatorial elections, this paper finds that Democratic candidates for governor with marginal victories opt to increase corrections spending as a portion of the total state expenditure, while Republican candidates decrease it. The local average treatment effect is approximately 0.2% increase of corrections expenditures with a close margin of victory for Democratic candidates. These results demonstrate how electoral incentives and party jointly impact criminal justice budgeting decisions.

Introduction

Corrections spending, that is, spending on police, prisons, and so on, seems to be an increasingly politicized issue. As a result, how does party affiliation of a candidate impact corrections spending? The hypothesis for this paper is that in states with close elections, winners within a small victory margin will devote a higher percentage of the state budget to corrections spending to satisfy the median voter. This paper uses regression discontinuity design (RDD) to test how party affiliation in close elections with governors impacts corrections spending within a given year for a state as a percentage of total state expenditures. In general, more conservative states tend to spend a greater amount on corrections. It has been found, though, that Democratic control of the state government generally has an insignificant or slightly negative impact of corrections spending.¹ For other types of spending, such as education, it has been found that spending fluctuates with election cycles. When a state election coincides with a presidential election, Democratic control of a state house will indicate reduced education spending, while in state elections not coinciding with presidential ones, Democratic control indicates an increase in education spending.² While party affiliation can be a determinant of support for specific types of expenditures, it is not the entire story, as candidates also face pressures from election cycles. Furthermore, there may be differences in incumbents as opposed to officials newly elected to a position. Incumbents better understand the institutional constraints of their positions, thus operate differently than newly elected officials, but also tend to have a greater advantage in elections.³ This paper differs from previous close election RDs in that it focuses on the role of

¹ Stucky, Thomas D, Karen Heimer, and Joseph B Lang. 2007. "A Bigger Piece of the Pie? State Corrections Spending and the Politics of Social Order."

² Chin, Mark J, and Lena Shi. 2025. "Average and Heterogeneous Effects of Political Party on State Education Finance and Outcomes: Regression Discontinuity Evidence across U.S. Election Cycles."

³ Lee, David S., Enrico Moretti, and Matthew J. Butler. 2002. "Do Voters Affect or Elect Policies? Evidence from the U.S. House."

the governor, which can often have a significant impact on the budget or act as a figurehead for the political party within the state, when it comes to corrections spending.

Data

The data for this analysis comes from two separate sources: one is the Urban Institute's State and Local Government Finance Data Tool, and the other is sourced from Harvard Dataverse, which is replication data for a paper title, "Partisanship & Nationalization in American Elections: Evidence from Presidential, Senatorial, & Gubernatorial Elections in the U.S. Counties, 1872-2020" by Algara and Amlani. The Urban Institute's data tool provided data on corrections spending as a fraction of total state expenditures. The replication data provided information on gubernatorial elections.

The "gov_elections_release" data frame was pulled from the dataset produced by Algara and Amlani. Then, grouping by the election id, which identified elections by year and state, the sum of democratic votes and sum of republican votes across the states' counties were taken. From these sums, the total votes for the election were found, along with the win margin for democratic candidates. A dummy variable was also produced for whether a democratic candidate won or not. To filter for only close elections, only elections with a win margin of an absolute value less than or equal to 5% were selected. This left 538 elections in the dataset for use.

The corrections data already only included the state name, the year, and the corrections spending as a fraction of total state expenditures. The abbreviation for the state name was added to join the corrections spending data to the close elections data, then the years were filtered for both datasets to be between 1977 and 2022, as the corrections spending data was only available for this time

frame. The data sets were joined by the state abbreviations and the year, leaving 119 observations for use.

This was then standardized using z-scores to make the data more consumable. Table 1 in the appendix provides statistics for the data. Lee et al (2004), which first looked at party control from close elections and effect on policy, only looked at junior legislators to eliminate incumbency effects. This paper does not discard incumbents; however, many states implement term limits for the executive.

Empirical Methodology

The rationale for using gubernatorial elections while looking at corrections spending is that when a new governor takes office, the budget is often a vital tool used to set policy goals and set the targets for the term. State corrections spending falls is recommended by the governor's administration, then approved or vetoed by the state house and senate. Corrections have become a political issue, especially as Republicans have increasingly sought to label themselves as "tough on crime", while liberal lawmakers have been more open to criminal reform. In areas with close elections, where the treatment is one party winning over the other, there may be a noticeable impact on corrections spending due to divisiveness or partisan animosity.

Regression discontinuity design is an effective method of measuring the differences at the cutoff. The treatment group and control group are only marginally different in RDD, so if a jump exists in the treatment group, then this suggests a trend that acts discontinuously, such that the arbitrary cutoff, or the treatment, is a determining factor in outcomes. There are many advantages to RDD, including strong internal validity, weaker assumptions necessary, and a clear framework that can

be graphed in a way that is consumable to readers.⁴ Continuing on weaker assumptions—other designs, such as matching or instrumental variable designs, depend on strong assumptions of causality.⁵ RDD does not require such a high level of assumption about the relationship between variables. Furthermore, if assumptions are held, then there is high credibility for causal inference.⁶ With datasets in which randomization is not feasible, RDD makes causal inference possible.⁷

The design is, however, not without fault. While it may have strong internal validity, sometimes the outcome is only valid at the cutoff or has limited external validity.⁸ RDD requires less assumptions, but datasets for analysis must be large to compensate. With the requirement for many samples near the threshold for precision, but the detail required in the data limiting it, data around the threshold is constrained, inhibiting statistical power.⁹ Lastly, RDD is highly sensitive to manipulation at various stages. In data collection, heaping can occur from bias in measurement¹⁰, while bandwidth selection in analysis can distort outcomes.¹¹

Considering the disadvantages, RDD is still the best method of analysis for this paper. In RD design for close elections, selecting within a small margin of victory for assigning treatment, which in this case would be winning the election, is nearly as robust as random sampling.¹² With

⁴ Imbens, Guido, and Thomas Lemieux. 2007. *Regression Discontinuity Designs : A Guide to Practice*. Cambridge, Massachusetts: National Bureau of Economic Research.

⁵ Lee, David S, and Thomas Lemieux. 2009. *Regression Discontinuity Designs in Economics*. Cambridge, Mass: National Bureau of Economic Research.

⁶ Ibid

⁷ Barreca, Alan I, Jason M Lindo, and Glen R Waddell. 2011. *Heaping-Induced Bias in Regression-Discontinuity Designs*.

⁸ Imbens, Guido, and Thomas Lemieux. 2007. *Regression Discontinuity Designs : A Guide to Practice*.

⁹ Lee, David S, and Thomas Lemieux. 2009. *Regression Discontinuity Designs in Economics*

¹⁰ Barreca, Alan I, Jason M Lindo, and Glen R Waddell. 2011.

¹¹ Imbens, Guido, and Thomas Lemieux. 2007. *Regression Discontinuity Designs : A Guide to Practice*.

¹² Lee, David S., Enrico Moretti, and Matthew J. Butler. 2002.

correct bandwidth selection, bias can be reduced and RDD can be a powerful tool for demonstrating the effect of Democratic electoral victory on corrections spending.

For this paper, a sharp RD is used. The cutoff for winning the election is exactly 50% of the vote, splitting dataset into two groups, one being those that won the election within 5% of the vote (treatment), and those that lost within 5% of the vote (control). The discontinuity estimator is expressed as the equation below:

$$\tau = \lim_{x \downarrow 0} \mathbb{E}[V | x] - \lim_{x \uparrow 0} \mathbb{E}[V | x]$$

This represents the vote share as a percentage for the Democratic candidate minus the vote share as a percentage for the Republican candidate, which ultimately is the margin of victory. The linear regression can be expressed as follows:

$$Y = \alpha + \beta_1 X + \beta_2 Z + \delta_1 (X \cdot Z) + \varepsilon$$

With Y being the amount spent on corrections as a fraction of total state expenditures, X being the win margin as expressed prior, with Democrat wins being coded as positive and Republican wins being coded as negative, and Z being a binary variable representing whether the candidate is Democratic or not, essentially if the group is being treated or not.

The McCrary Density Test can help test for endogeneity by looking for manipulation of the running variable, in the case of this paper, the win margin, near the cutoff, which is 50% of votes. The test can assist in detecting sorting, or potential endogenous treatment. The McCrary Density Test for this section is detailed in Appendix B by Figure 4. It shows no significant change in density, suggesting that there is likely not sorting around the cutoff. The assumption can be made that the selection of those treated is nearly as powerful as random sampling.

Generally, close elections are thought to be driven by exogenous factors rather than inherent differences between candidates, thus the idea that an RD would create a random selection of nearly identical candidates to treat. While this section has tested for endogeneity in some capacity, ultimately, winning as the determinant to treatment can be exogenous.

Results

When looking at the data, more close elections occur during midterm years and a similar effect with education spending seems to be occurring with corrections, in which spending is adjusted based on the election cycle; these are shown in Figures 2 and 3 in Appendix B, respectively. The results are congruent with the hypothesis that Democratic candidates in close elections may choose to devote more of state expenditures to corrections following their electoral victory. On the other hand, Republican candidates in close elections decrease spending on corrections following victory.

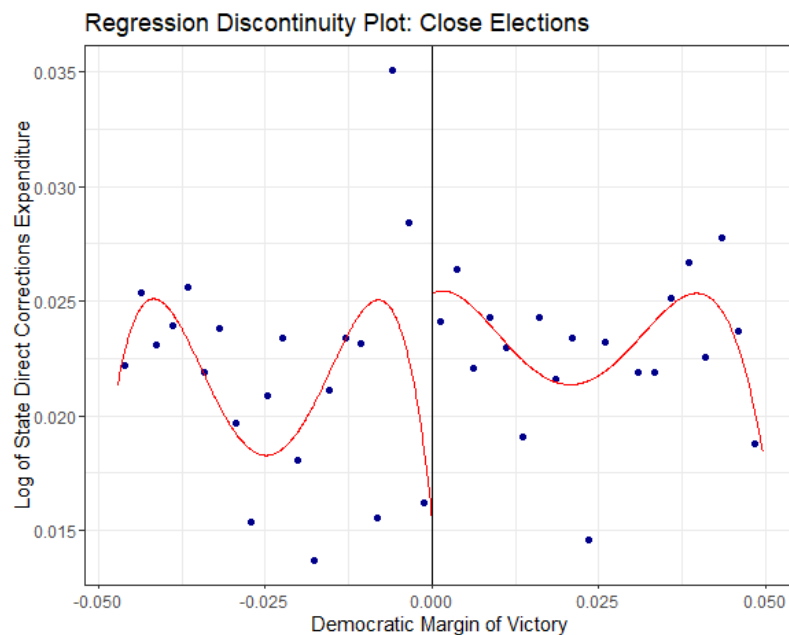


Figure 1: RD Plot with Bandwidth of 0.009 (Greater than Optimal) for Visualizing Results

Figure 1, plotting the results of the RD, show evenly spaced mean variance optimal bandwidth selection to avoid bias that can occur from mean

squared error bandwidth selection.¹³ The optimal bandwidth is quite narrow, being 0.007, for visualization purposes, Figure 1 displays the results with a bandwidth of 0.009, Figure 5 with the optimal bandwidth of 0.007 as determined using Coverage Error Rate optimal bandwidth.

Table 2 in Appendix A shows the coefficients of both the weighted and unweighted regressions. They are virtually identical but still share insight into the impact that the covariate and the interaction between the Democratic margin of victory and binary variable determining party affiliation. This binary variable does represent recipients of treatment and determines the local average treatment effect, which is 0.002 in both the weighted and unweighted models. Win margin had the greatest impact on corrections spending, while whether the candidate the Democratic or not had an impact of lower magnitude. This suggests that one of the determining factors in budget allocation towards corrections spending as a percentage of state expenditures would be the margin of victory for the candidate—essentially how universally popular said candidate is with the public.

Robustness Checks

There are a couple robustness checks that can be performed on the model to verify the results, however, in this section, specifically polynomial order checks and bandwidth sensitivity checks will be performed. Regression discontinuity estimates are highly sensitive to the choice of bandwidth, so it is important to optimize bandwidth selection based on the data set.¹⁴ Close

¹³ De Magalhães, Leandro, Dominik Hangartner, Salomo Hirvonen, Jaakko Meriläinen, Nelson A. Ruiz, and Janne Tukiainen. 2025. "When Can We Trust Regression Discontinuity Design Estimates from Close Elections? Evidence from Experimental Benchmarks."

¹⁴ de la Cuesta, Brandon, and Kosuke Imai. 2016. "Misunderstandings About the Regression Discontinuity Design in the Study of Close Elections."

election RDs can be particularly ridden with issues, such as assuming randomization, over-relying on difference-in-means tests, and including too many tests that do not demonstrate anything significant. A suggested solution by de la Cuesta and Imai (2016) is using a local linear regression with optimized bandwidths.¹⁵ When performing this bandwidth sensitivity analysis, the results in Figure 6 in Appendix B show that 0.007 is indeed the optimal bandwidth, which was selected using CERRD, or coverage error-rate optimal bandwidth selector in the rrobust package. This evaluates the dataset to choose an appropriate bandwidth and minimize bias. This continues to reaffirm that there is an uptick in corrections spending by Democrats that win in close elections, but even more so, there is a sharper decrease in spending by Republicans.

Literature on RDD also suggests using lower-order polynomials within narrow bandwidths selected via CERRD to check the robustness of the RD.¹⁶ By fitting different polynomial orders to the data, the robustness of the treatment effect can be tested, particularly due to the fact that manipulation can occur through overfitting with high-degree polynomials. Table 3 in Appendix A shows the results of this check, with each being indistinguishable from the last. The bandwidth may be too narrow to show any variation with different polynomial orders; however, this is reassuring for the results. As the model changes, the results local to the cutoff are stable. The identification problem that could be caused by a jump in the covariate is solved in this way, as the model remains stable suggesting that the driving force is the running variable of the win margin for Democrats.

¹⁵ de la Cuesta, Brandon, and Kosuke Imai. 2016.

¹⁶ De Magalhães, Leandro, Dominik Hangartner, Salomo Hirvonen, Jaakko Meriläinen, Nelson A. Ruiz, and Janne Tukiainen. 2025.

Conclusion

This paper has explored how party affiliation in closely contested gubernatorial elections impacts corrections spending as a share of state expenditures using RDD for analysis. By utilizing the randomness that arises in close elections as a proxy for true random sampling, this analysis examines the causal effect of Democratic victory in close elections over Republicans for governor seats on corrections spending. The results suggest that Democratic victories in close elections are associated with a modest increase in corrections spending, whereas Republican victories tend to lead to noticeable reductions. These findings support the hypothesis that Democratic candidates who win narrow elections may respond to perceived median voter preferences and electoral pressures but also supplements this with information about how Republican victors respond as well, which is likely also reducing spending to match the preferences of the median voter. The fact that the treatment effect persists across linear, quadratic, cubic and quartic model specifications with considerable stability within a narrow bandwidth that has been optimized and tested for sensitivity suggests internal validity of the results. While the analysis is clear and consistent in its main result, some limitations persist. The narrow bandwidth needed for valid identification limits external validity, and potential variation due to institutional differences across states is beyond the scope of the analysis. Regardless, the results are robust. With a local average treatment effect of 0.002, the plausible effect size of the treatment is a 0.2% increase in corrections spending as a fraction of total state expenditures when there is a Democratic victor in a close election. While the figure seems small, when in context of state budgets, this is not an insignificant amount of money.

Given the assumed sensitivity of corrections spent to party control and electoral margins based on the analysis, policymakers, as well as the general public, should understand how many

budgetary decisions are shaped by electoral incentives. This may suggest that there should be more oversight into the budget-making process, or rather a more technocratic approach to ensure the effectiveness of a budget, especially on something as important and impactful as corrections. Furthermore, the finding that Republican governors reduce corrections spending more sharply than Democrats increase it suggests that “tough on crime” rhetoric may not always translate to higher budget allocations. This could be further explored by examining how campaign messaging aligns with post-election behavior, particularly in close elections.

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Appendix A: Tables

Table 1: Summary of Statistics for Data

Summary Statistics for Close Elections Dataset					
Statistic	N	Mean	St. Dev.	Min	Max
year	118	1,998.983	12.716	1,978	2,020
dvote	118	917,360.300	819,087.800	69,972	4,043,723
rvote	118	923,062.700	830,028.300	67,595	4,076,186
total_votes	118	1,840,423.000	1,647,866.000	137,567	8,119,909
dem_win	118	0.492	0.502	0	1
win_margin	118	-0.002	0.029	-0.047	0.050
total_cor_dir_exp	118	0.023	0.008	0.010	0.052

Table 2: Regression Discontinuity Results

	Weighted	Unweighted
Win Margin	-0.026	-0.026
	(0.077)	(0.077)
Democratic Win (Binary)	0.002	0.002
	(0.003)	(0.003)
Interaction Term	0.018	0.018
	(0.107)	(0.107)
Num.Obs.	118	118
R2	0.006	0.006
R2 Adj.	-0.021	-0.021
AIC	-796.6	-796.6
BIC	-782.7	-782.8
Log.Lik.	403.293	403.313
F	0.213	0.213
RMSE	0.01	0.01

Results of RD

Table 3: Robustness Check Using Lower Order Polynomials to Check Fit

	Linear (p=1)	Quadratic (p=2)	Cubic (p=3)	Quartic (p=4)
Democratic Win Margin	-0.026	-0.026	-0.026	-0.026
	(0.077)	(0.077)	(0.077)	(0.077)
Democratic Win (Binary)	0.002	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)
Interaction Term		0.018	0.018	0.018
		(0.107)	(0.107)	(0.107)
Num.Obs.	118	118	118	118
R2	0.006	0.006	0.006	0.006
R2 Adj.	-0.021	-0.021	-0.021	-0.021
AIC	-796.6	-796.6	-796.6	-796.6
BIC	-782.8	-782.8	-782.8	-782.8
Log.Lik.	403.313	403.313	403.313	403.313
F	0.213	0.213	0.213	0.213
RMSE	0.01	0.01	0.01	0.01

RD Estimates by Polynomial Order

Appendix B: Figures

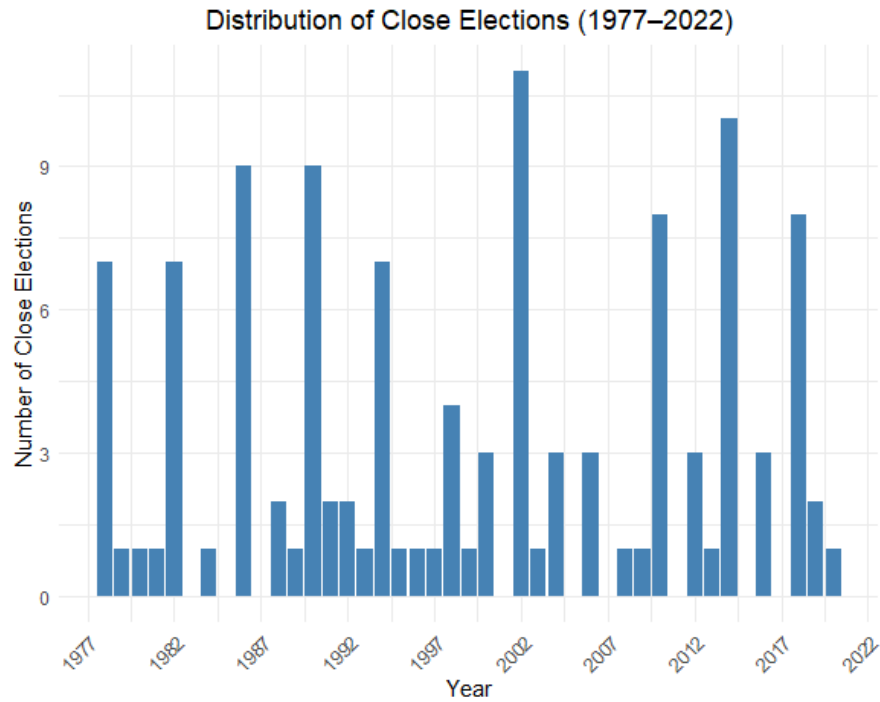


Figure 2: Distribution of Close Elections Over Time

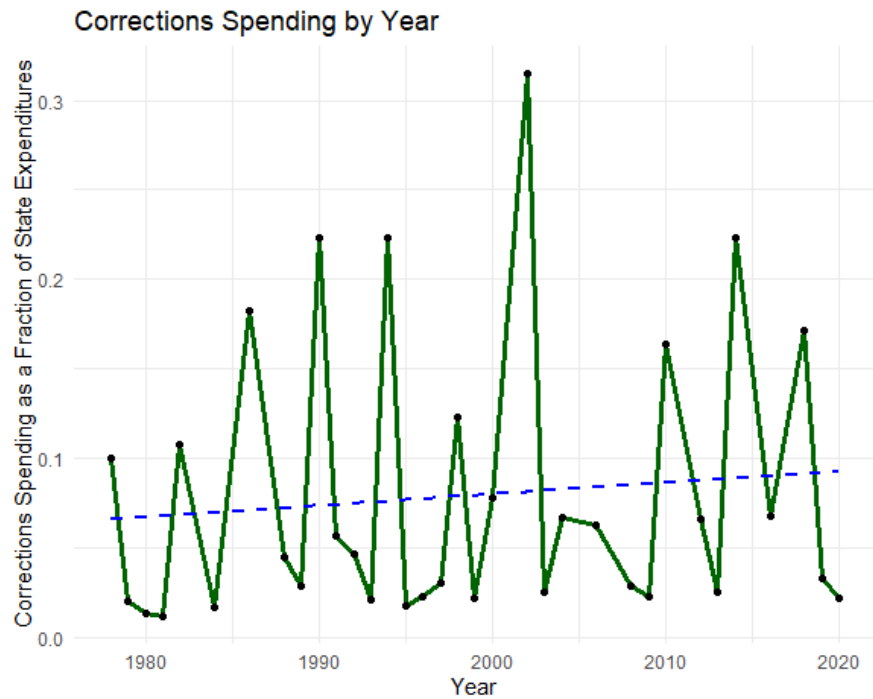


Figure 3: Corrections Spending by Year

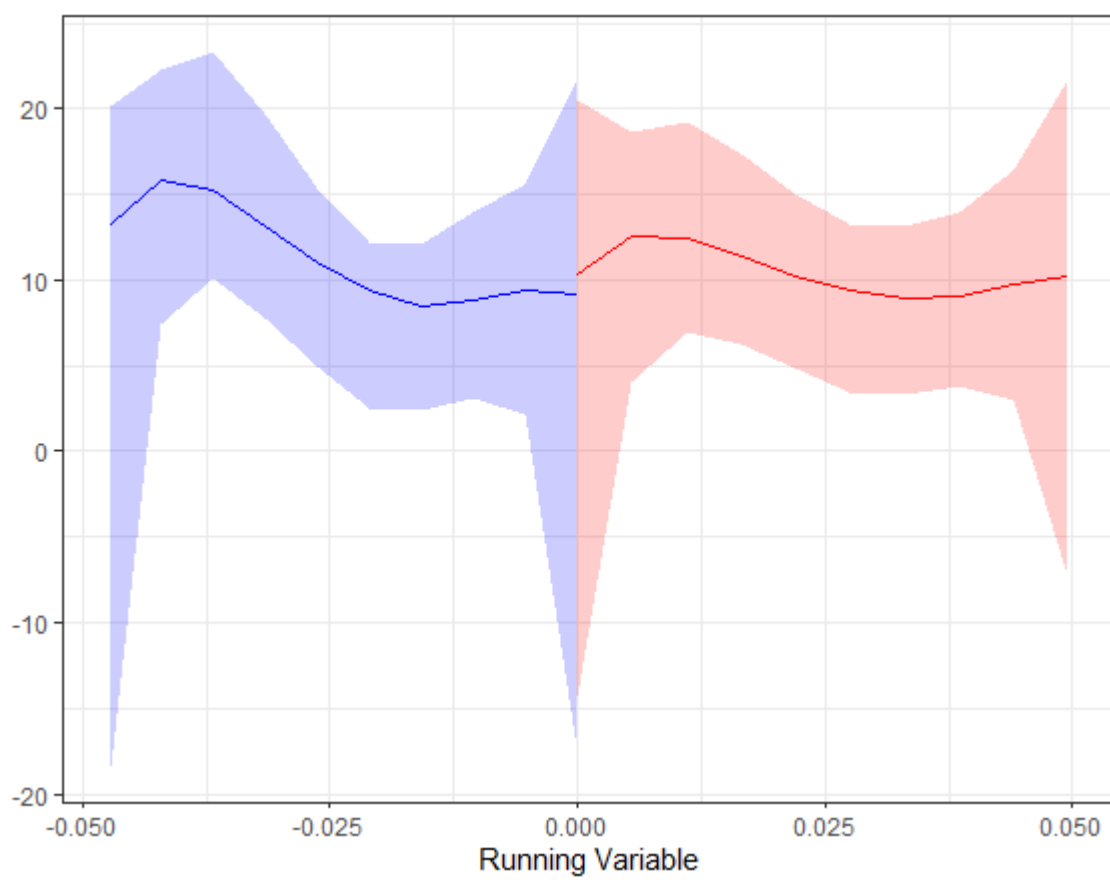


Figure 4: McCrory Density Test Results

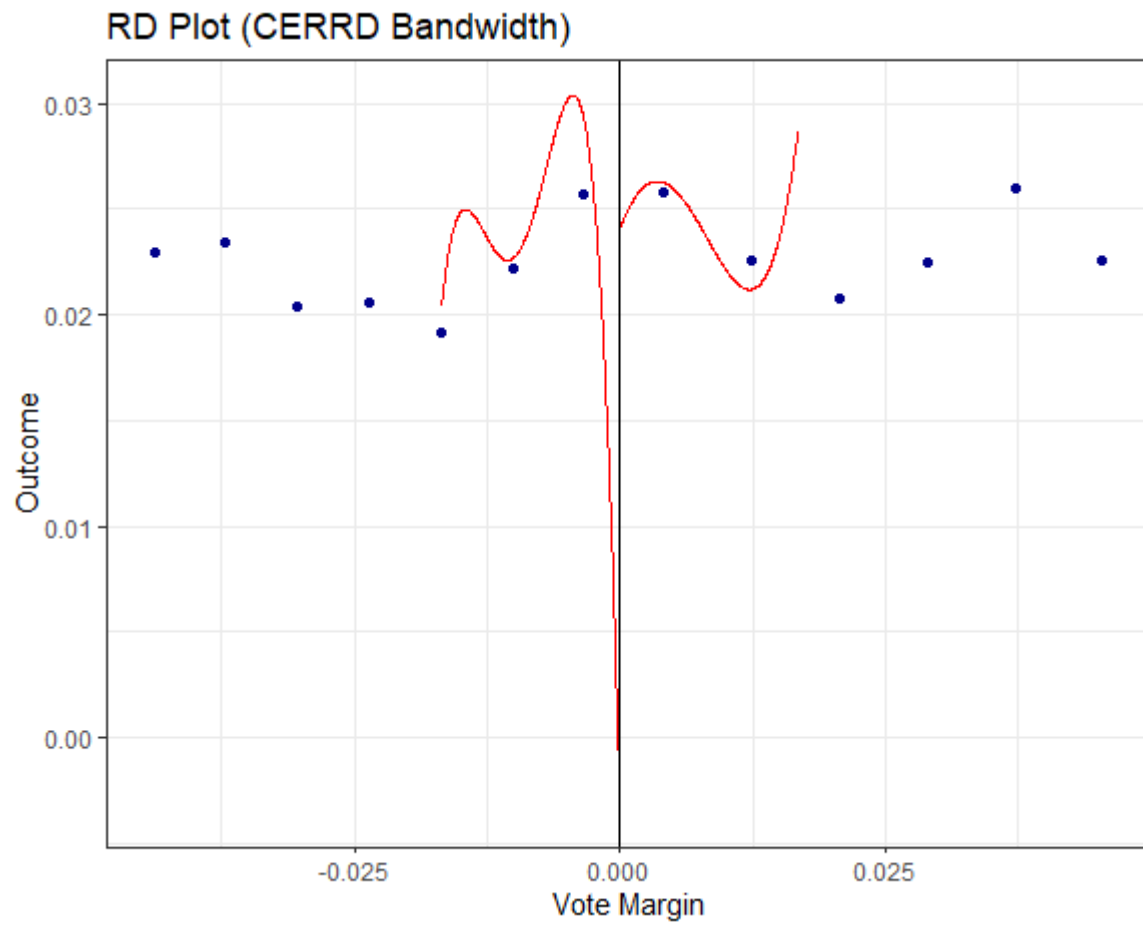


Figure 5: RD Results Plotted with Optimal Bandwidth of 0.007

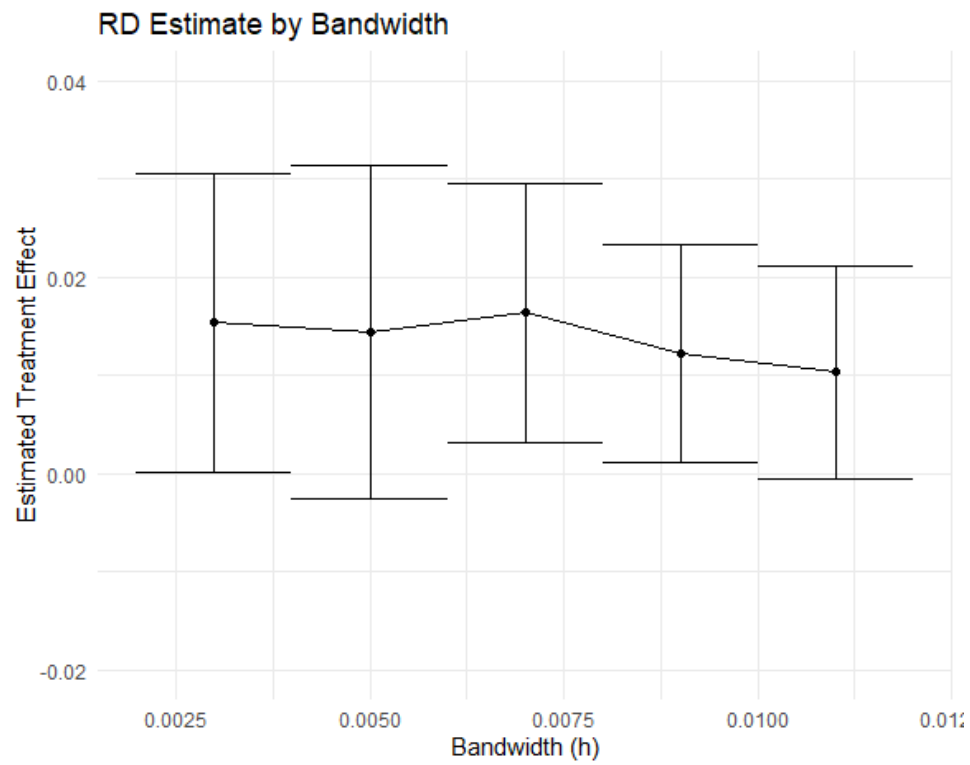


Figure 6: Bandwidth Analysis