Assignment 5 Question 1

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(a)

The assumptions underlying the RDD in this paper are that in order for the school to attain autonomy (GM) there must be a 50% vote from the community to have the school be GM. Clark also assumes that the school performance, test scores, is increasing in autonomy and school effort. Schools that are already GM at the start of a period are fully autonomous and therefore decide only how much effort to exert. Effort in turn improves school performance, test scores for example, but effort is costly. Schools that are not GM at the start period must decided how much effort to exert and whether or not to become Gm. For given effort, non GM schools performance is assumed lower than GM school performance; hence schools have an incentive to become GM. There are cost associated with GM status and the decision to become one is non trivial.

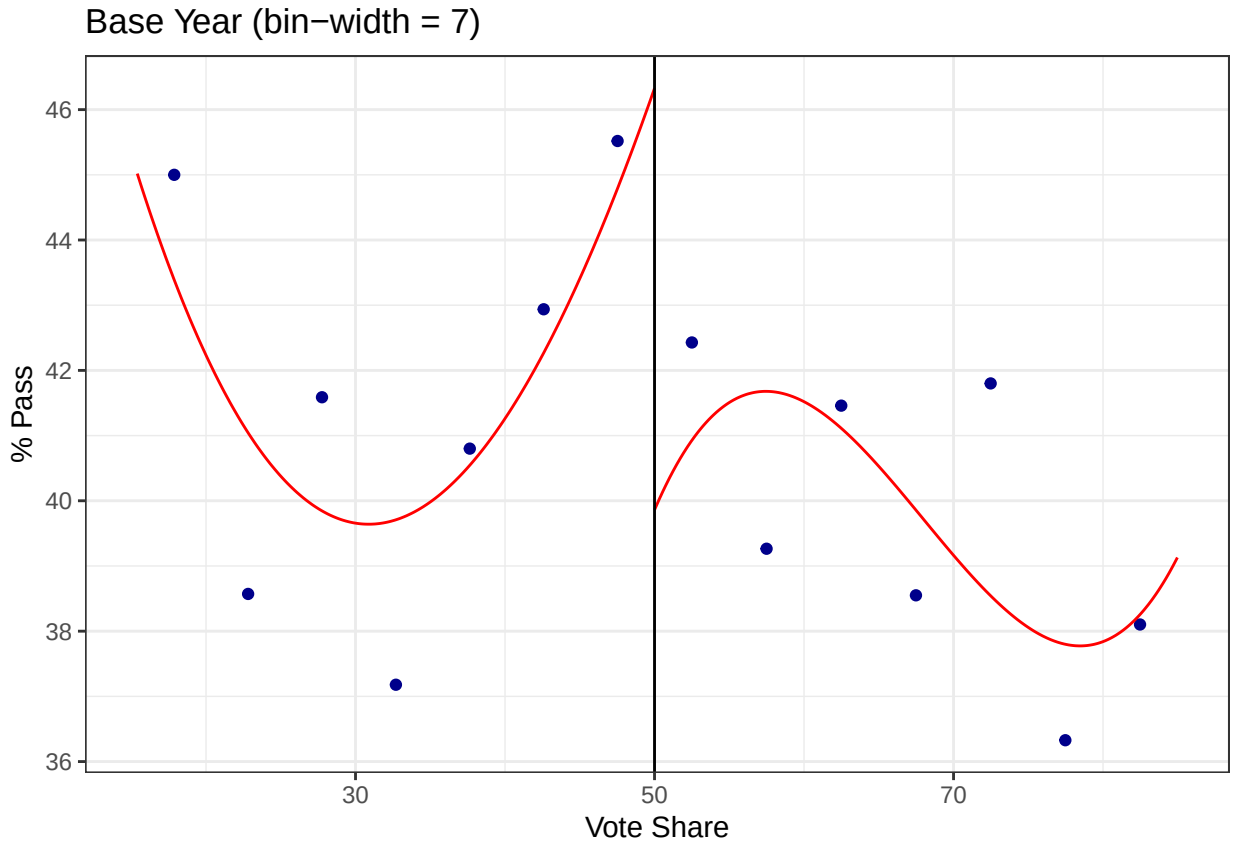
The conceptual framework assumed that schools were identical. In practice, schools differ along many dimensions, and certain types of school may be more likely to hold and win a GM vote (e.g., those with more entrepreneurial head teachers). Clark's empirical approach overcomes this selection problem by focusing on the jump in performance among schools at the 50 percent win threshold. Specifically, Clark considers variants of the fuzzy regression discontinuity model for school i voting on GM

(b)

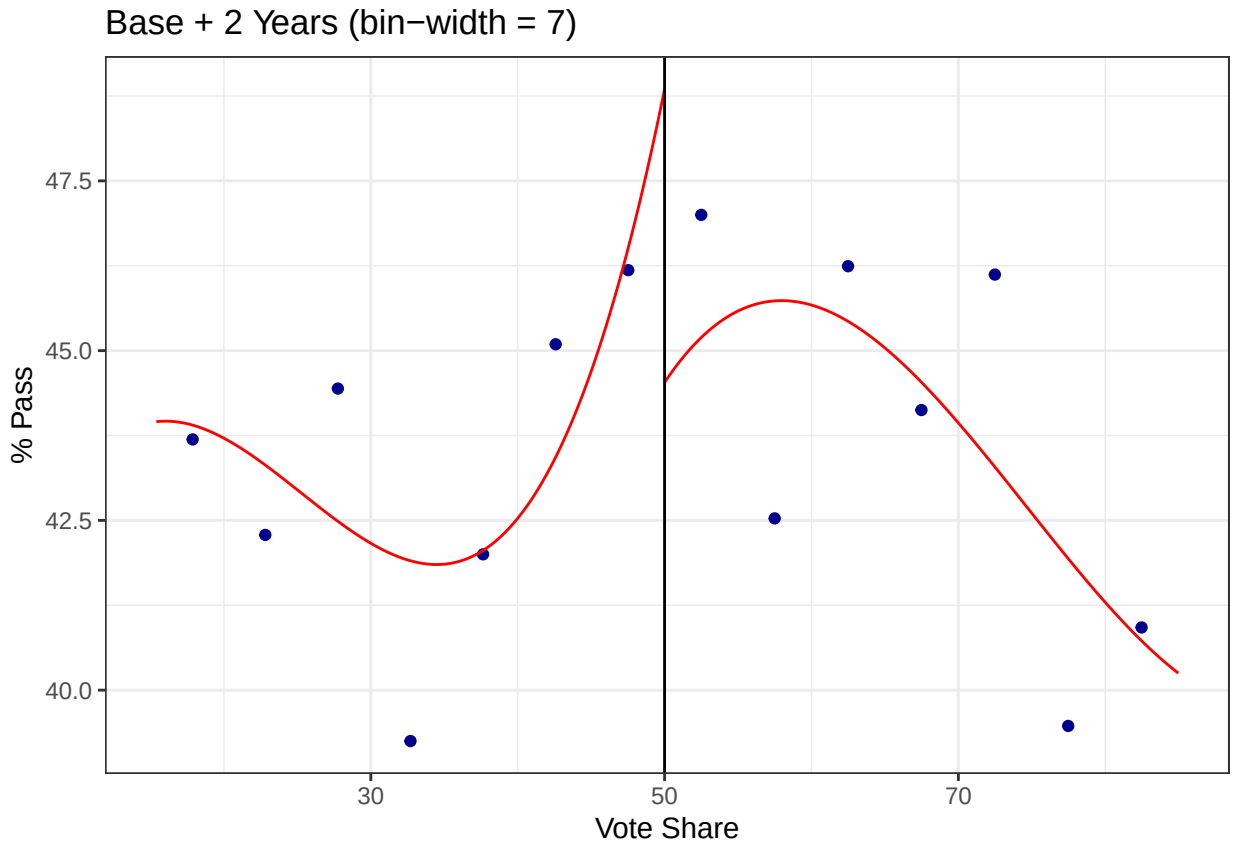
These figures represent figure 8 from the paper. They are all visualizing:

The Impact of GM Status on Schools that Become Grant-Maintained

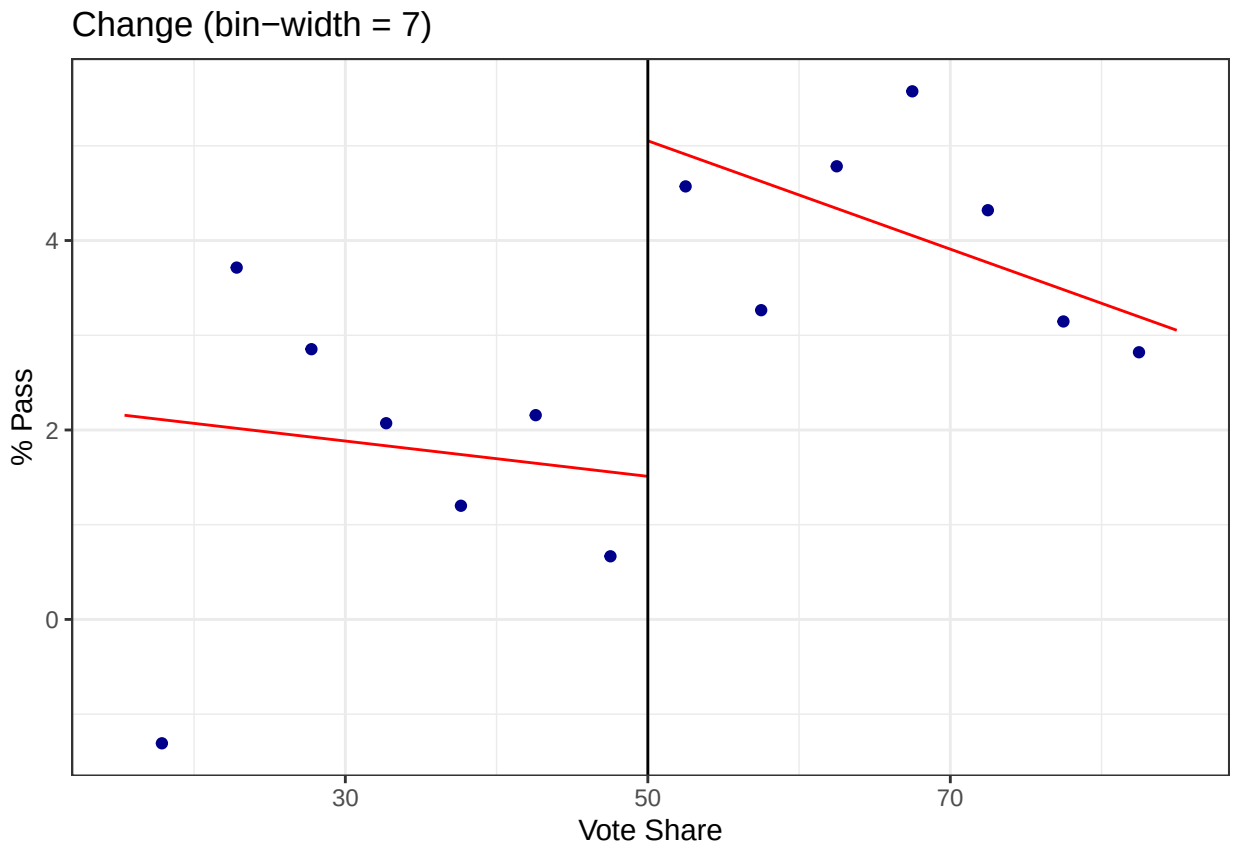
```r
# Restricting Data to (15,85)
restrict = subset(damon, vote <= 85 & vote >= 15)

# calculating the % change
restrict$percentage_change = restrict$passrate2 - restrict$passrate0

# Base Year
rdplot(y = restrict$passrate0, x = restrict$vote , c = 50, p = 3, nbins = 7, title = "Base Year (bin-width = 7)", x.l
```



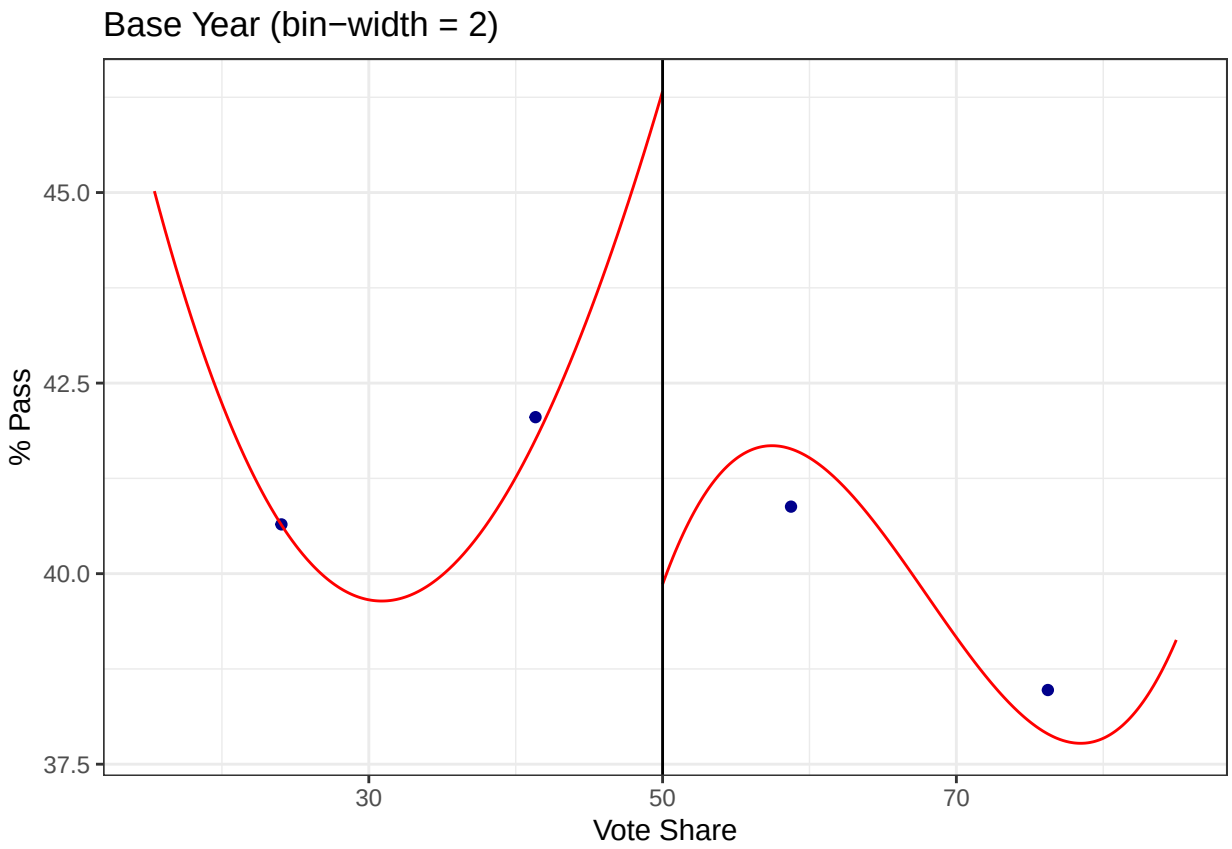
```r
# Base +2 Year
rdplot(y = restrict$passrate2, x = restrict$vote, c = 50, p = 3, nbins = 7, title = "Base + 2 Years (bin-width = 7)",
```



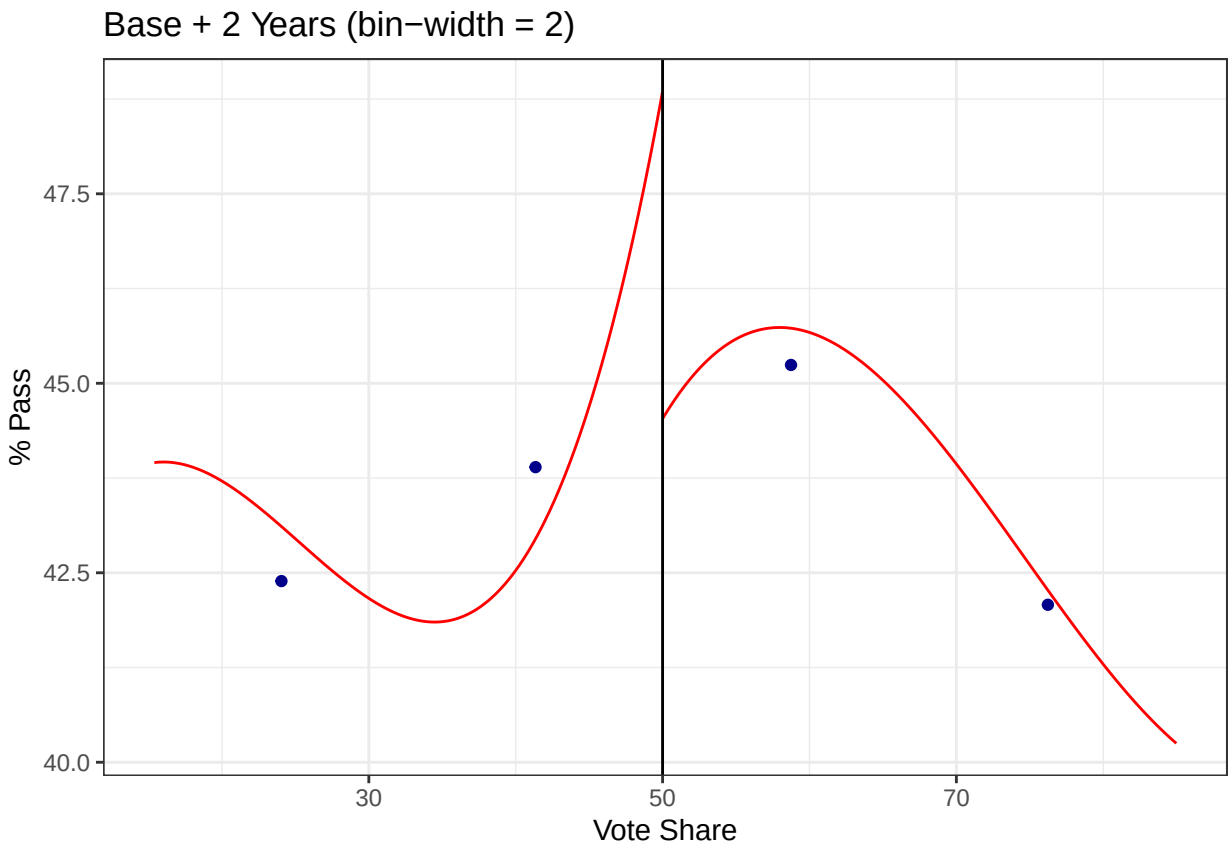

```r
# % change
rdplot(y = restrict$percentage_change, x = restrict$vote, p = 1, nbins = 7, c = 50, title = "Change (bin-width = 7)",
```



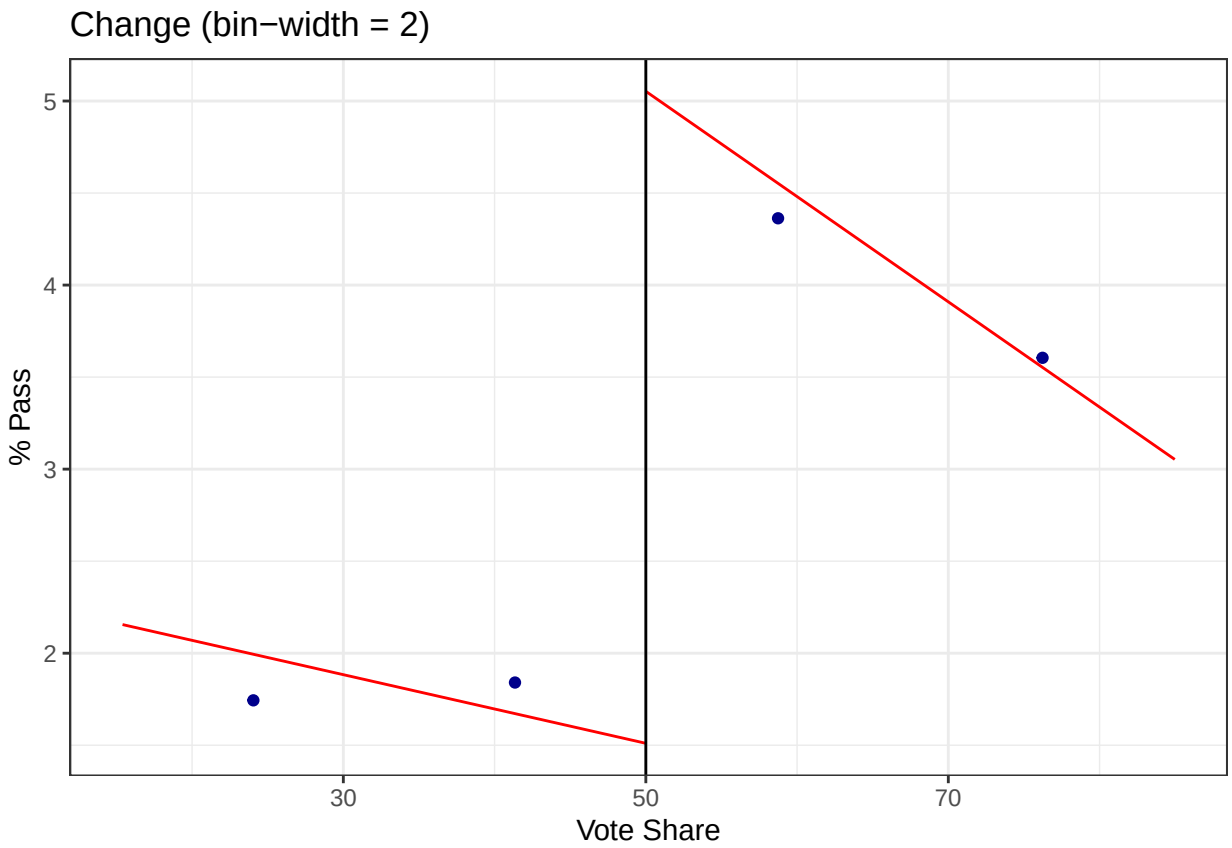

```
# Base Year
rdplot(y = restrict$passrate0, x = restrict$vote , c = 50, p = 3, nbins = 2, title = "Base Year (bin-width = 2)", x.l
```




```
# Base +2 Year
rdplot(y = restrict$passrate2, x = restrict$vote, c = 50, p = 3, nbins = 2, title = "Base + 2 Years (bin-width = 2)",
```




```
# % change
rdplot(y = restrict$percentage_change, x = restrict$vote, p = 1, nbins = 2, c = 50, title = "Change (bin-width = 2)",
```



From the graphs above we can see that as you decrease the bin size from 7 which is what Clark uses in the paper for Figure 8. We can see that there is no difference in terms of the lines of best fit, however, we can better visualize the data with a higher bin width. We see more of the data points.

(c)

Clark restricts his sample to those schools with votes from 15% and 85% because he wants to reduce bias from outliers from schools who were very opposed or very for autonomy. For example schools with high vote shares may have been under threat of closure, whilst few schools received very low vote shares. Additionally, RD necessitates that in order to estimate the average

effect of a treatment you look at an arbitrary cutoff and evaluate the treatment effects before and after the cutoff. Additionally they saw that schools outside this interval have different baseline characteristics and are less likely to survive. Clark needs to estimate around the cutoff, 50, which is inside the (15,85) interval. Other columns have functions of vote share because vote share is the forcing variable in this Fuzzy Regression Discontinuity model. Fuzzy RD exploits discontinuities in the probability of treatment conditional on a variate. The discontinuity, here is Vote share, and it becomes the IV for the treatment status. Which is why Table 3a includes functions of vote share both on their own and interacted with the win/lose variable.

(d)

```
##
## % Table created by stargazer v.5.2.2 by Marek Hlavac, Harvard University. E-mail: hlavac at fas.harvard.edu
## % Date and time: Mon, Feb 21, 2022 - 09:07:34
## % Requires LaTeX packages: dcolumn
## \begin{table}[!htbp] \centering
##   \caption{Regression Results (d)}
##   \label{}
## \begin{tabular}{@{\extracolsep{5pt}}lD{.}{.}{-3} D{.}{.}{-3} D{.}{.}{-3} D{.}{.}{-3} }
## \\[-1.8ex]\hline
## \hline \\[-1.8ex]
##  & \multicolumn{4}{c}{\textit{Dependent variable:}} \\
## \cline{2-5}
## \\[-1.8ex] & \multicolumn{4}{c}{passrate2 - passrate0} \\
## \\[-1.8ex] & \multicolumn{1}{c}{(1)} & \multicolumn{1}{c}{(2)} & \multicolumn{1}{c}{(3)} & \multicolumn{1}{c}{(4)}
## \hline \\[-1.8ex]
##  win & 2.091^{***} & 3.716^{***} & 3.542^{***} & 2.654 \\
##   & (0.635) & (1.283) & (1.320) & (2.015) \\
##   & & & & \\
##  margin &  & -0.045 &  &  \\
##   &  & (0.031) &  &  \\
##   & & & & \\
##  win\_margin &  &  & -0.057 & 0.191 \\
##   &  &  & (0.037) & (0.155) \\
```

```
##   & & & & \\
##  lose\_margin &  &  & -0.019 & -0.135 \\
##   &  &  & (0.056) & (0.220) \\
##   & & & & \\
##  win\_margin\_squared &  &  &  & -0.007^{*} \\
##   &  &  &  & (0.004) \\
##   & & & & \\
##  lose\_margin\_squared &  &  &  & -0.004 \\
##   &  &  &  & (0.007) \\
##   & & & & \\
##  Constant & 1.800^{***} & 1.096 & 1.510 & 0.853 \\
##   & (0.503) & (0.697) & (1.007) & (1.567) \\
##   & & & & \\
## \hline \\[-1.8ex]
## Observations & \multicolumn{1}{c}{524} & \multicolumn{1}{c}{524} & \multicolumn{1}{c}{524} & \multicolumn{1}{c}{52
## R$^{2}$ & \multicolumn{1}{c}{0.020} & \multicolumn{1}{c}{0.024} & \multicolumn{1}{c}{0.025} & \multicolumn{1}{c}{0
## Adjusted R$^{2}$ & \multicolumn{1}{c}{0.018} & \multicolumn{1}{c}{0.021} & \multicolumn{1}{c}{0.019} & \multicolum
## Residual Std. Error & \multicolumn{1}{c}{7.025 (df = 522)} & \multicolumn{1}{c}{7.018 (df = 521)} & \multicolumn{1
## F Statistic & \multicolumn{1}{c}{10.842$^{***}$ (df = 1; 522)} & \multicolumn{1}{c}{6.494$^{***}$ (df = 2; 521)} &
## \hline
## \hline \\[-1.8ex]
## \textit{Note:}  & \multicolumn{4}{l}{$^{*}$p$<$0.1; $^{**}$p$<$0.05; $^{***}$p$<$0.01} \\
##  & \multicolumn{4}{l}{Standard errors in parentheses} \\
## \end{tabular}
## \end{table}
```

Table 1: Regression Results (d)

	Dependent variable:			
	passrate2 - passrate0			
	(1)	(2)	(3)	(4)
win	2.091***	3.716***	3.542***	2.654
	(0.635)	(1.283)	(1.320)	(2.015)
margin		−0.045		
		(0.031)		
win_margin			−0.057	0.191
			(0.037)	(0.155)
lose_margin			−0.019	−0.135
			(0.056)	(0.220)
win_margin_squared				−0.007*
				(0.004)
lose_margin_squared				−0.004
				(0.007)
Constant	1.800***	1.096	1.510	0.853
	(0.503)	(0.697)	(1.007)	(1.567)
Observations	524	524	524	524
R^2	0.020	0.024	0.025	0.031
Adjusted R^2	0.018	0.021	0.019	0.021
Residual Std. Error	7.025 (df = 522)	7.018 (df = 521)	7.022 (df = 520)	7.015 (df = 518)
F Statistic	10.842*** (df = 1; 522)	6.494*** (df = 2; 521)	4.432*** (df = 3; 520)	3.270*** (df = 5; 518)
Note:	*p<0.1; **p<0.05; ***p<0.01			
	Standard errors in parentheses			

- I attempted to estimate the some regressions where vote was squared, but I got slightly different results. I attribute this to a lack of data. We lack the data that is required to obtain certain regression results. We cannot control for all the treatments and controls mentioned in the empirical section of the paper where it mentions the design behind each regression column. However, here is the design of all the columns:
- Column 1 describes the mean improvement difference between winners and losers, column 2 adds a control for vote share, and column 3 interacts vote share with win (the specification used to generate the fitted lines in Figure 8). In column 4 they weight according to the size of the school exam-taking cohort, to give more weight to schools with more exam-takers (to the extent the model is correctly specified). In column 5 Clark uses a quadratic vote share control function and the estimated impact of winning falls. This is not surprising given the degree of concavity in the (50,85) interval (Figure 8), although a cubic fit would be expected to pick up this shape (and the dip to the left of the 50% threshold). In the interests of parsimony, since the baseline levels are relatively flat and Clark have no priors regarding the appropriate functional form, Clark reverts to the linear specification. His preferred estimates are in column 6.
- If RDD is internally valid there must be $E[Y_{0i}|X_i]$ and $E[Y_{1i}|X_i]$ are continuous in X_i at the cutoff X_0. Here we can see that one of our interaction terms was statistically significant. This means that the assumption for internal validity holds because if our interaction terms all had a high degree of statistical significance then our win variable has a different effect on the passrate depending on margin and vote.

(e)

```
# Sampling smaller thresholds (95, 5)
restrict = subset(damon, vote <= 75 & vote >= 25)

model_d_1 <- lm(passrate2-passrate0 ~ win, data=restrict)
model_d_2 <- lm(passrate2-passrate0 ~ win + margin, data=restrict)
model_d_3 <- lm(passrate2-passrate0 ~ win + win_margin + lose_margin, data=restrict)
model_d_4 <- lm(passrate2-passrate0 ~ win + win_margin + lose_margin + win_margin_squared + lose_margin_squared, data

stargazer(model_d_1, model_d_2, model_d_3, model_d_4, title="Regression Results (e)", align=TRUE, notes = "Standard e
```

```
##
```

```
## % Table created by stargazer v.5.2.2 by Marek Hlavac, Harvard University. E-mail: hlavac at fas.harvard.edu
## % Date and time: Mon, Feb 21, 2022 - 09:07:35
## % Requires LaTeX packages: dcolumn
## \begin{table}[!htbp] \centering
##   \caption{Regression Results (e)}
##   \label{}
## \begin{tabular}{@{\extracolsep{5pt}}lD{.}{.}{-3} D{.}{.}{-3} D{.}{.}{-3} D{.}{.}{-3} }
## \\[-1.8ex]\hline
## \hline \\[-1.8ex]
##  & \multicolumn{4}{c}{\textit{Dependent variable:}} \\
## \cline{2-5}
## \\[-1.8ex] & \multicolumn{4}{c}{passrate2 - passrate0} \\
## \\[-1.8ex] & \multicolumn{1}{c}{(1)} & \multicolumn{1}{c}{(2)} & \multicolumn{1}{c}{(3)} & \multicolumn{1}{c}{(4)}
## \hline \\[-1.8ex]
##  win & 2.724^{***} & 2.799^{*} & 2.945^{*} & 2.290 \\
##   & (0.757) & (1.550) & (1.561) & (2.421) \\
##   & & & & \\
##  margin &  & -0.003 &  &  \\
##   &  & (0.052) &  &  \\
##   & & & & \\
##  win\_margin &  &  & 0.034 & 0.023 \\
##   &  &  & (0.068) & (0.273) \\
##   & & & & \\
##  lose\_margin &  &  & -0.053 & 0.102 \\
##   &  &  & (0.080) & (0.338) \\
##   & & & & \\
##  win\_margin\_squared &  &  &  & 0.0004 \\
##   &  &  &  & (0.010) \\
##   & & & & \\
##  lose\_margin\_squared &  &  &  & 0.006 \\
##   &  &  &  & (0.013) \\
##   & & & & \\
```

```
##  Constant & 1.801^{***} & 1.765^{**} & 1.131 & 1.829 \\
##   & (0.561) & (0.865) & (1.158) & (1.885) \\
##   & & & & \\
## \hline \\[-1.8ex]
## Observations & \multicolumn{1}{c}{357} & \multicolumn{1}{c}{357} & \multicolumn{1}{c}{357} & \multicolumn{1}{c}{35
## R$^{2}$ & \multicolumn{1}{c}{0.035} & \multicolumn{1}{c}{0.035} & \multicolumn{1}{c}{0.037} & \multicolumn{1}{c}{0
## Adjusted R$^{2}$ & \multicolumn{1}{c}{0.032} & \multicolumn{1}{c}{0.030} & \multicolumn{1}{c}{0.029} & \multicolum
## Residual Std. Error & \multicolumn{1}{c}{7.120 (df = 355)} & \multicolumn{1}{c}{7.130 (df = 354)} & \multicolumn{1
## F Statistic & \multicolumn{1}{c}{12.941$^{***}$ (df = 1; 355)} & \multicolumn{1}{c}{6.454$^{***}$ (df = 2; 354)} &
## \hline
## \hline \\[-1.8ex]
## \textit{Note:}  & \multicolumn{4}{l}{$^{*}$p$<$0.1; $^{**}$p$<$0.05; $^{***}$p$<$0.01} \\
##  & \multicolumn{4}{l}{Standard errors in parentheses} \\
## \end{tabular}
## \end{table}
```

Table 2: Regression Results (e)

	Dependent variable:			
	passrate2 - passrate0			
	(1)	(2)	(3)	(4)
win	2.724***	2.799*	2.945*	2.290
	(0.757)	(1.550)	(1.561)	(2.421)
margin		−0.003		
		(0.052)		
win_margin			0.034	0.023
			(0.068)	(0.273)
lose_margin			−0.053	0.102
			(0.080)	(0.338)
win_margin_squared				0.0004
				(0.010)
lose_margin_squared				0.006
				(0.013)
Constant	1.801***	1.765**	1.131	1.829
	(0.561)	(0.865)	(1.158)	(1.885)
Observations	357	357	357	357
R^2	0.035	0.035	0.037	0.038
Adjusted R^2	0.032	0.030	0.029	0.024
Residual Std. Error	7.120 (df = 355)	7.130 (df = 354)	7.133 (df = 353)	7.151 (df = 351)
F Statistic	12.941*** (df = 1; 355)	6.454*** (df = 2; 354)	4.525*** (df = 3; 353)	2.746** (df = 5; 351)
Note:	*p<0.1; **p<0.05; ***p<0.01			
	Standard errors in parentheses			

- When I experimented with a threshold of smaller [25,75] I get slightly different results compared to my results previously from (d) and they also differ from Clark's results. Here there is a tradoff between bias and efficiency. We have fewer estimators that are statistically significant because we have less observations. This makes our estimators less precise. But we experience less bias from outliers in the data when we make our threshold smaller.

(f)

```
restrict = subset(damon, vote <= 85 & vote >= 15)

model_f_1 <- lm(passrate0 ~ win, data = restrict )

stargazer(model_f_1, title="Regression Results (f)", align=TRUE, notes = "Standard errors in parentheses", notes.alig
```

```
##
## % Table created by stargazer v.5.2.2 by Marek Hlavac, Harvard University. E-mail: hlavac at fas.harvard.edu
## % Date and time: Mon, Feb 21, 2022 - 09:07:35
## % Requires LaTeX packages: dcolumn
## \begin{table}[!htbp] \centering
##   \caption{Regression Results (f)}
##   \label{}
## \begin{tabular}{@{\extracolsep{5pt}}lD{.}{.}{-3} }
## \\[-1.8ex]\hline
## \hline \\[-1.8ex]
##  & \multicolumn{1}{c}{\textit{Dependent variable:}} \\
## \cline{2-2}
## \\[-1.8ex] & \multicolumn{1}{c}{passrate0} \\
## \hline \\[-1.8ex]
##  win & -2.082 \\
##   & (1.364) \\
##   & \\
##  Constant & 41.462^{***} \\
```

```
##   & (1.081) \\
##   & \\
## \hline \\[-1.8ex]
## Observations & \multicolumn{1}{c}{524} \\
## R$^{2}$ & \multicolumn{1}{c}{0.004} \\
## Adjusted R$^{2}$ & \multicolumn{1}{c}{0.003} \\
## Residual Std. Error & \multicolumn{1}{c}{15.093 (df = 522)} \\
## F Statistic & \multicolumn{1}{c}{2.329 (df = 1; 522)} \\
## \hline
## \hline \\[-1.8ex]
## \textit{Note:}  & \multicolumn{1}{l}{$^{*}$p$<$0.1; $^{**}$p$<$0.05; $^{***}$p$<$0.01} \\
##  & \multicolumn{1}{l}{Standard errors in parentheses} \\
## \end{tabular}
## \end{table}
```

Table 3: Regression Results (f)

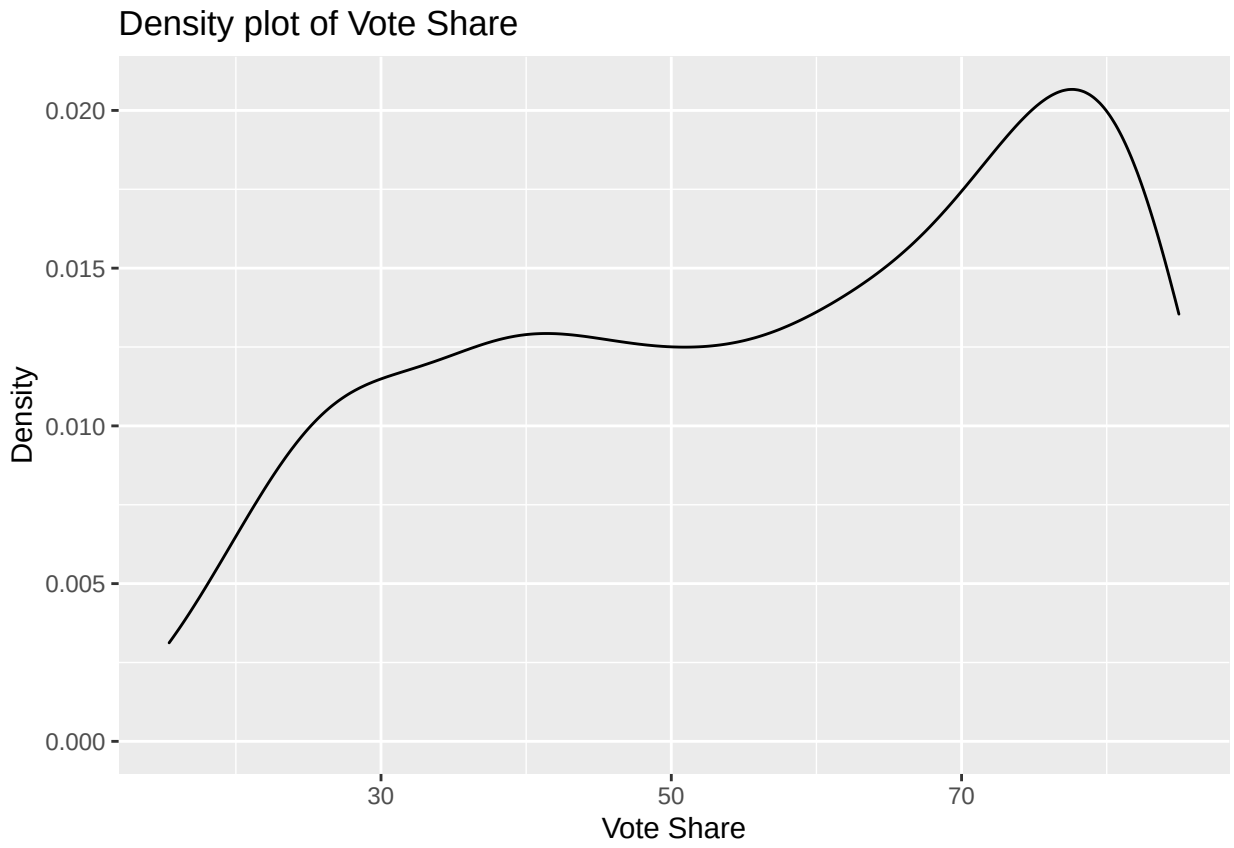
	Dependent variable:
	passrate0
win	−2.082
	(1.364)
Constant	41.462***
	(1.081)
Observations	524
R^2	0.004
Adjusted R^2	0.003
Residual Std. Error	15.093 (df = 522)
F Statistic	2.329 (df = 1; 522)
Note:	*p<0.1; **p<0.05; ***p<0.01
	Standard errors in parentheses

There is no reason to use passrate0 as the dependent variable as we want to estimate the effect of the autonomy of schools on pass rate. The vote would have had little to now effect on the pass rate in the base year. The base year is important because we can regress the difference in the base year + 2 with the base year to get a significant result. This does not invalidate the results. The result here is that on average a school that has one the election has a %200 reduction in pass rate. This result is not statistically significant and therefore does not affect nor invalidate our RDD.

(g)

In addition to points e and f we can include further evidence about the relationship between the variables. We can see here that there is not much difference between the amount of observations before the 50% cutoff and after the cutoff. If there was a large difference then it would invalidate our RDD because it would mean that assignment of the treatment versus control is not as good as randomly assigned.

```r
restrict = subset(damon, vote <= 85 & vote >= 15)
ggplot(data = restrict, aes(vote)) +
  geom_density()+
  labs(title = "Density plot of Vote Share") +
  xlab("Vote Share") +
  ylab("Density")
```



(h)

The validity of RD estimates depends crucially on the assumption that the polynomials provide and adequate representation of E [Y0i | Xi] If not what looks like a jump may simply be a non-linearity in f (Xi) that the polynomials have not accounted for. A regression discontinuity method is close to an experiment under ideal conditions, in reducing selection bias (high internal validity), and in presenting challenges to broader generalization (low external validity).

(i)

```
rdrobust(restrict$passrate2-restrict$passrate0, restrict$vote, c=50)
```

```
## Call: rdrobust
##
## Number of Obs.                  524
## BW type                       mserd
## Kernel                   Triangular
## VCE method                       NN
##
## Number of Obs.                  195         329
## Eff. Number of Obs.              59          66
## Order est. (p)                    1           1
## Order bias  (q)                   2           2
## BW est. (h)                   9.678       9.678
## BW bias (b)                  15.263      15.263
## rho (h/b)                     0.634       0.634
## Unique Obs.                     193         326
```

```
restrict_rd <- subset(restrict, vote > 50 - 9.678 & vote < 50 + 9.678)

model_1_i <- lm(passrate2-passrate0 ~ win, data=restrict_rd)
stargazer(model_1_i, title="Regression Results (f)", align=TRUE, notes = "Standard errors in parentheses", notes.alig
```

```
##
```

```
## % Table created by stargazer v.5.2.2 by Marek Hlavac, Harvard University. E-mail: hlavac at fas.harvard.edu
## % Date and time: Mon, Feb 21, 2022 - 09:07:35
## % Requires LaTeX packages: dcolumn
## \begin{table}[!htbp] \centering
##   \caption{Regression Results (f)}
##   \label{}
## \begin{tabular}{@{\extracolsep{5pt}}lD{.}{.}{-3} }
## \\[-1.8ex]\hline
## \hline \\[-1.8ex]
##  & \multicolumn{1}{c}{\textit{Dependent variable:}} \\
## \cline{2-2}
## \\[-1.8ex] & \multicolumn{1}{c}{passrate2 - passrate0} \\
## \hline \\[-1.8ex]
##  win & 2.571^{*} \\
##   & (1.367) \\
##   & \\
##  Constant & 1.475 \\
##   & (0.993) \\
##   & \\
## \hline \\[-1.8ex]
## Observations & \multicolumn{1}{c}{125} \\
## R$^{2}$ & \multicolumn{1}{c}{0.028} \\
## Adjusted R$^{2}$ & \multicolumn{1}{c}{0.020} \\
## Residual Std. Error & \multicolumn{1}{c}{7.628 (df = 123)} \\
## F Statistic & \multicolumn{1}{c}{3.538$^{*}$ (df = 1; 123)} \\
## \hline
## \hline \\[-1.8ex]
## \textit{Note:}  & \multicolumn{1}{l}{$^{*}$p$<$0.1; $^{**}$p$<$0.05; $^{***}$p$<$0.01} \\
##  & \multicolumn{1}{l}{Standard errors in parentheses} \\
## \end{tabular}
## \end{table}
```

Table 4: Regression Results (f)

	Dependent variable:
	passrate2 - passrate0
win	2.571*
	(1.367)
Constant	1.475
	(0.993)
Observations	125
R^2	0.028
Adjusted R^2	0.020
Residual Std. Error	7.628 (df = 123)
F Statistic	3.538* (df = 1; 123)
Note:	*p<0.1; **p<0.05; ***p<0.01
	Standard errors in parentheses

(j)

I used this package for b so my results are the same. One thing that I noticed is that when you increase the binwidth the data collapses and you miss certain nuances in the visualization. The opposite is true when you decrease it.