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1. Randomized control trials (RCT), Regression Discontinuity (RD), and Difference-in-Differences methods (DID) are all statical analysis tools used to estimate the treatment effect of a model based on the experiment type.

   Randomized control trials (RCT) is an experiment model that attempts to control for selection bias by randomly assigning participants to the treatment group. RCT is ideal for providing unbiased estimates of the causal effects of the treatment on the outcome variable and can estimate both the average treatment effect (ATE) and the local average treatment effect (LATE). This differs from RD and DD due to these two models using preassigned groups based on either a predetermined threshold value (RD), or a difference in two groups over time (DID).

   Regression Discontinuity (RD) is a quasi-experimental pretest-posttest design that uses a cut-off for the intervention that is assigned. The model then compares the regression on either side of this cut-off to measure the discontinuity around the intervention. This design provides an estimate for the LATE but is unable to provide an estimate for ATE. Witch differs from RCT which provides both.

   Difference-in-Difference (DID) is a analysis method that compares the outcomes of two groups overtime. The assumption of this model is that the changes in these two groups would be the same if no treatment was implemented. DID provides an unbiased estimate of ATE and LATE like RCT but unlike RD. The main difference between RCT and DID is the assignment of the two groups. DID and RD differs because DID is reliant on observing the same groups over time.

2. Columns 1 and 3: Ma = alpha + ρDa + $\boldsymbol{\gamma}$age
   Columns 2 and 4: Ma = alpha + ρDa + $\boldsymbol{\gamma}$age + $\boldsymbol{\gamma}$age^2 + ρDa*age^2
   a. See figure replication in appendix for Table 4.1, Figure 4.2, and Figure 4.4
      i. Regression Discontinuity (RD) measures the estimated effect of implementing a minimum legal drinking age of 21 and its effects on death rates. For us to have causal inference we must make sure our model is statistically significantly different from zero. To test significance, we use standard errors by comparing our coefficients to their stand errors. Generally, we use the rule that if our coefficients are twice as large as their standard errors, we assume significance. The larger our estimate is the larger the impact the treatment effect will have. The coefficient for all deaths per 100,000 per 30 days (Table 4.1) is 7.66, witch when compared to its standard error of 1.51 we find that this coefficient is statistically significant.

         One restriction of RD is only being able to estimate the local average treatment effect (LATE). This narrow bandwidth restriction restricts the amount we can generalise about the estimated effects from our model to a limited range. This

contrasts with the estimation power we can get from DID and RTC which would give us average treatment effects (ATE).

ii. Columns 1 and 2 use a higher bandwidth than columns 3 and 4 with 1 and 2 spanning the age range 19-22 and 3 and 4 spanning the age range 20-21. Columns 1 and 3 only use age as the regressor whereas columns 2 and 4 uses age, age squared interacted with age over twenty-one. Columns 1 and 2 use a wider bandwidth than columns 3 and 4. Comparing columns 1 and 3 to 2 and 4 we see that the additional interaction terms did not have a large effect on the estimated coefficients raising the total death rate from 7.66 to 9.55 for 19-22 and 9.75 to 9.61 for ages 20-21.

iii. To check the concerns that the RD estimates may be non-linear effects instead of discontinuity we narrowed our observation to near the cut-off. Since we have enough estimations around the cut-off, we can rule out the data being a nonlinear model. Restricting our model to check for this, however, does reduce our sample size and increase our standard errors which is lowering the accuracy of our analysis.

b. See figure 5.2. Our Difference-in-Difference (DID) estimate standard errors that are large enough for us to make a statistically significant claim that legal access to alcohol increases the likelihood of death. The DID estimates the ATE as long as the assumption holds that parallel trends exist between the death rate of people under and over 21 assuming no access to alcohol for anyone.

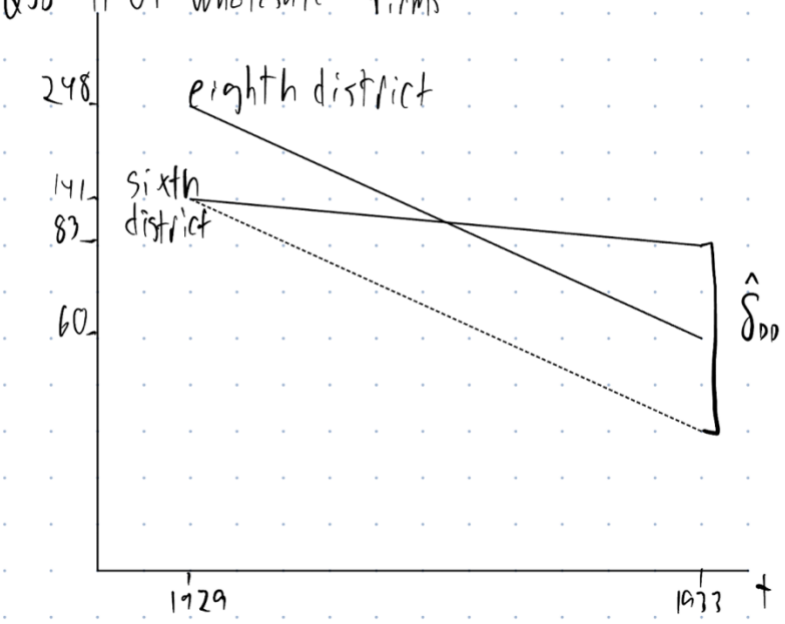
c. Columns 1 and 3 in our RD model in table 4.1 compared to the DID column 1 which has no weight or state trends we find the DID coefficient is larger than the two RD coefficients by a small amount.

3.

Q3A

$$\hat{\delta}_{DD} = (\bar{Y}_2^A - \bar{Y}^A) - (\bar{Y}_2^B - \bar{Y}_1^B)$$
$$= (641 - 783) - (607 - 930)$$
$$= 181$$

Q3B



$$\hat{\delta}_{DD} = (\bar{Y}_2^A - \bar{Y}^A) - (\bar{Y}_2^B - \bar{Y}_1^B)$$
$$= (60 - 141) - (83 - 245)$$
$$= 81$$

Appendix:

Table 4.1

Table 4.1

Sharp RD estimates of MLDA effects on mortality

	Ages 19-22		Ages 20-21	
	(1)	(2)	(3)	(4)
All	7.663***	9.548***	9.753***	9.611**
	(1.514)	(2.108)	(2.064)	(3.491)
Motor Vehicle Accidents	4.534***	4.663***	4.759***	5.892***
	(0.717)	(1.114)	(1.082)	(1.989)
Suicide	1.794***	1.814**	1.724**	1.297
	(0.496)	(0.773)	(0.733)	(1.104)
Homicide	0.104	0.200	0.164	-0.453
	(0.450)	(0.599)	(0.589)	(0.982)
Other External Causes	0.441	1.178***	0.831**	1.346***
	(0.292)	(0.343)	(0.368)	(0.403)
Internal	0.392	1.073	1.692**	1.249
	(0.543)	(0.817)	(0.745)	(1.086)
Alcohol	0.442**	0.799**	0.740**	1.028*
	(0.206)	(0.334)	(0.333)	(0.579)
Controls	age	age, age^2, interacted with over -21	age	age, age^2, interacted with over -21
sample size	48	48	24	24

Figure 4.2

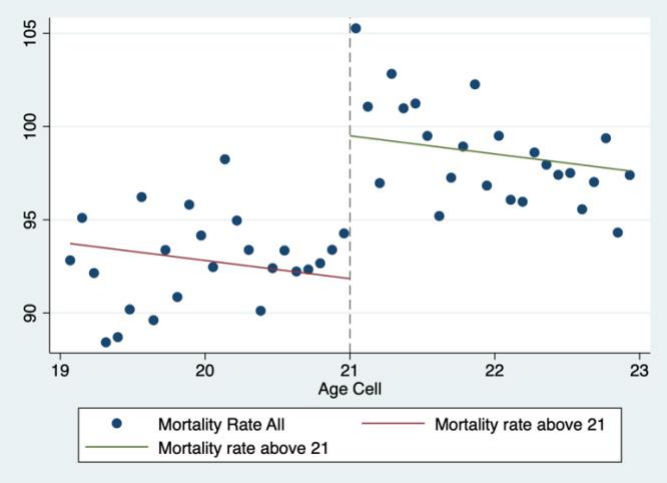


Figure 4.4

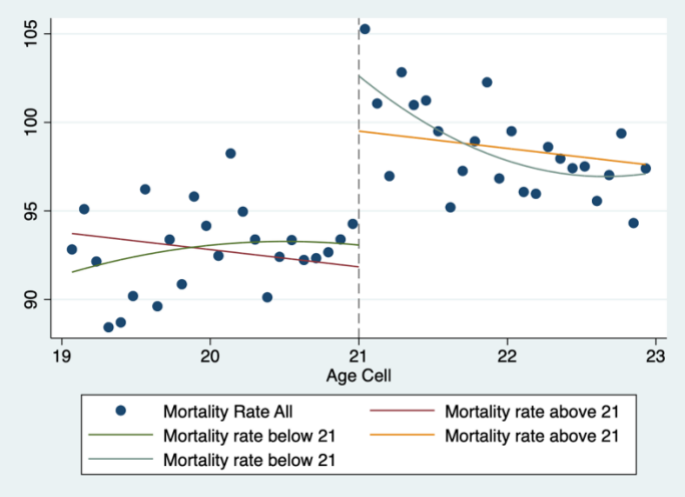


Table 5.2

Table 5.2
Regression DD estimates of MLDA effects on death rates

Dependent Variables	(1)	(2)	(3)	(4)
All Deaths	10.804**	8.467	12.413***	9.649**
	(4.592)	(5.098)	(4.599)	(4.643)
MVA	7.592***	6.644**	7.499***	6.461***
	(2.496)	(2.656)	(2.267)	(2.240)

Suicide	0.591	0.474	1.485*	1.255
	(0.590)	(0.795)	(0.882)	(0.892)
All Internal Causes	1.333	0.079	1.894	1.284
	(1.586)	(1.933)	(1.779)	(1.445)
State Trends	No	Yes	No	Yes
Weights	No	No	Yes	Yes