A/B Testing- Homework 3

Question #1

The coefficients do not represent the causal effect of attending catholic school on the 12^{th} grade standardized math score attainment because in addition to the covariates shared in the list, there are other unobservable factors that may have an impact on the 12^{th} grade standardized math score that we have not accounted for. This creates a backdoor where unobservable factors (ϵ) affect our independent and dependent variables in our regression model. These observable factors can be divided into three categories as things that change over time for all subjects, test taker in this case (time trends), different things that change for different students but do not change over time (individual fixed effects) and things that change differently for different subjects over time ($z_{i,t}$). We can improve our results for this question by accounting for individual fixed effects and first differences that will bring us closer to the true value of causal effects, however, we can still cannot compute causal effects as $z_{i,t}$ would remain unknown and cannot be calculated. There may also be other fixed effects and time trends other than the ones shared that could impact our outcome variable. Given this, we can conclude that the results obtained using OLS may be hardly interpreted as the causal effect of attending a catholic school on the math scare in the 12th grade.

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factor(race)api	7.966***	1.833***
	(0.757)	(0.453)
factor(race)black	-2.493***	-0.367
raccor (raccy) brack	(0.694)	(0.419)
		(****
factor(race)hispanic	0.905	1.196***
	(0.678)	(0.402)
factor(race)white	4.311***	0.769**
ractor (race)witte	(0.604)	(0.358)
	(0.00.)	(0.330)
factor(parmar8)divorced		0.543
		(0.585)
5-1(0.224
factor(parmar8)married		-0.334 (0.542)
		(0.342)
factor(parmar8)never married		0.336
		(0.778)
factor(parmar8)separated		-0.103
		(0.692)
factor(parmar8)widowed		0.140
		(0.799)
2999		-0.469
		(0.968)
14999		0.245
11333		(0.832)
19999		0.312
		(0.855)
24000		0.288
24999		0.288 (0.845)
		(0.013)
34999		0.732
		(0.837)
1000		0.005
4999		-0.025 (0.972)
		(0.372)

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7499		0.357 (0.900)
faminc80ne		0.968 (1.443)
49999		0.995 (0.839)
74999		0.798 (0.850)
9999		0.264 (0.883)
factor(fathed8)coll < 4		1.455*** (0.335)
factor(fathed8)coll grad		1.330*** (0.302)
factor(fathed8)doctorate		1.299** (0.511)
factor(fathed8)dont k0w		0.978*** (0.320)
factor(fathed8)hs grad		0.566** (0.238)
factor(fathed8)junior coll		0.949*** (0.296)
factor(fathed8)masters		1.279*** (0.381)
factor(hsgrad)1	8.972*** (0.420)	3.129*** (0.258)
factor(riskdrop8)1		-0.384** (0.189)
factor(riskdrop8)2		-0.758** (0.328)

	3,			
factor(riskdrop8)2			-0.758**	
			(0.328)	
factor(riskdrop8)3			-1.446***	
			(0.475)	
factor(riskdrop8)4			-1.787**	
· acco. (· co.ca. opc) ·			(0.806)	
factor(riskdrop8)5			-0.494	
raccor (r Eskar opoys			(1.989)	
factor(mothed8)coll < 4			0.724**	
raceor (moericao)corr < +			(0.336)	
factor(mothed8)coll grad			0.776**	
ractor(motheda)cott grad			(0.319)	
6 1 6 11 100 1 1			0.070	
factor(mothed8)doctorate			0.970 (0.622)	
6 . 6 .1 10 1 . 10				
factor(mothed8)dont k0w			0.141 (0.343)	
factor(mothed8)hs grad			0.174 (0.241)	
factor(mothed8)junior coll			0.615** (0.301)	
			(0.301)	
factor(mothed8)masters			0.265 (0.405)	
			(0.405)	
Constant	50.645***	39.817***	8.150***	
	(0.132)	(0.703)	(1.129)	
01	F 671	F C71	F 674	
Observations R2	5,671 0.016	5,671 0.168	5,671 0.715	
Adjusted R2	0.016	0.167	0.712	
Residual Std. Error		8.674 (df = 5663)		
F Statistic	90.481*** (df = 1; 5669) 1	l63.038*** (df = 7; 5663) 3 	327.63/*** (df = 43; 5627)	
Note: *p<0.1; **p<0.05; ***p<0.01				
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> #identify matched sample
> MyData.match <- data.table(match.data(Match))
> Matched.ids <- MyData$id %in% MyData.match$id
> MyData[, match := Matched.ids]
> Matched.ids.sum <- MyData$id %in% MyData.match$id
> MyData[, match := Matched.ids.sum]
> table(MyData$match)

FALSE TRUE
4549 1122
> |
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Question #2

In cases where randomization is not possible for any reason, we resort to natural experiment where selection is part of the experiment so there are factors that are inherently different between treatment and control group. Due to these differences, we cannot compute causal differences as they not only account for the effect of treatment on subject i, it also accounts for the selection bias (underlying differences) between the control and treatment group.

In natural experiments, in order to get closer to causal effects, we restrict our analysis only to units of analysis that are similar "to begin with" between control and treatment groups with the hope that these are also similar within the unobservable group too. This restricted group serves as a sub-population and returns better estimate for average treatment effect. In this example, we restrict our analysis to 8th grade standardized scores as these scores are expected to be similar among groups who attended catholic school (treatment) and who did not attend catholic school.

To check our propensity score, we use the nearest neighbor matching algorithm and run ttest to check whether there is a significant difference between the means of two groups. We can see that we were able to do one-to-one matching for 561 subjects in our dataset for control and treated group. As we re-run our regression for matched sample, we can see that get close to our causal effect as before doing this matching exercise, the effect of attending catholic school on math12 score is overestimated (coefficient is 3.895) while we see this coefficient coming down to 1.6601 when we run our regression on matched sample only which brings us closer to understanding the causal effect of attending catholic school on math12 score but it is still not entirely causal due to reasons discussed in Q1. This overestimation is mainly attributed to the effect of unobservable factors that are not accounted for while running our regression.