Econometrics 2 2019/20

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Final Assignment - Suggested solutions

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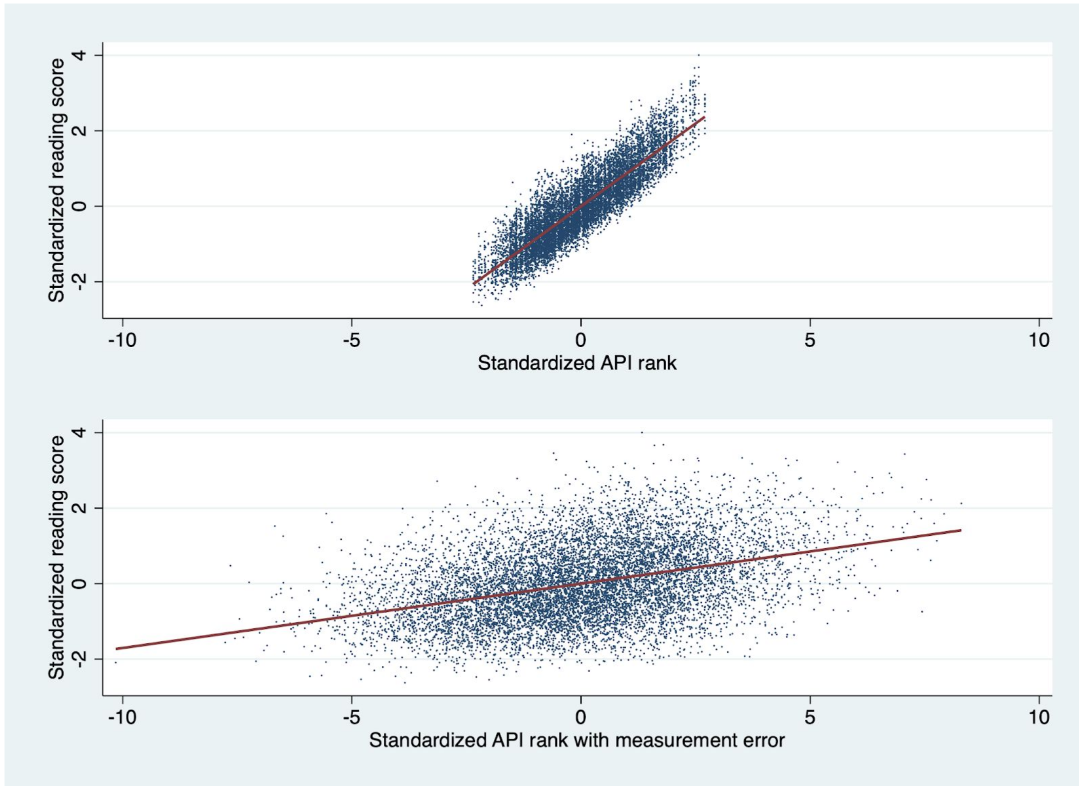
1.
   a. A seed allows us to get the exact replications of our results every time we run the code with the same seed. (And changing the seed can be a sort of a robustness check.)
   b. Standardization makes results easier to interpret and compare.
   c. The R^2 is the same in both regressions, 0.77. In a simple regression, the R^2 is the square of the correlation coefficient between the two variables, so we should not be surprised that they are the same. This has no implication for causal inference at all.
      (If you run *correlate api_rank readingscore*, you can check that the R^2 is indeed the square of the correlation coefficient. And note that the correlation coefficient is equal to the $\widehat{\beta}$ from the regressions—this is due to standardization.)
   d. This variable is API rank measured with an error. The estimated slope coefficient in 0.88 in the first regression and 0.17 in the second. When we have measurement error in the regressor, the slope coefficient is biased towards zero. This is known as attenuation bias. (See derivation in *Measurement error* slides 3-7.)

Graphic illustration (this is something extra, not part of the required solution):



(Code for the figure:

```
twoway (scatter readingscore api_rank, msize(vtiny)) (lfit readingscore api_rank, lwidth(medthick)), legend(off) name(basic, replace)
twoway (scatter readingscore api_error, msize(vtiny)) (lfit readingscore api_error, lwidth(medthick)), legend(off) name(error, replace)
graph combine basic error, xcommon rows(2)
```
)

Yes, it can be tested formally.

$$Z = \frac{\beta_1 - \beta_2}{\sqrt{(SE\beta_1)^2 + (SE\beta_2)^2}}$$

We have a large sample, so we can use a Z table for critical values. The test statistic is around 113, so the two coefficients are different at any usual level of significance.

Stata code to obtain the t-value:

```
reg  readingscore api_rank
```

```
scalar beta1=_b[api_rank]
scalar var1=_se[api_rank]^2

reg  readingscore api_error
scalar beta2=_b[api_error]
scalar var2=_se[api_error]^2

disp "t: " (beta2-beta1)/(sqrt(var1+var2))
```

e. We create another version of the API rank variable which has measurement error above the true mean but not below.
f. The coefficient is 0.29, so it does not coincide with them, it is between the two coefficients we previously saw. This measurement error depends on the level of the original variable, hence, CME assumptions do not hold.
g. A measurement error with the same variance but a positive mean shifts the whole distribution of x to the right, so intuitively, this should decrease the intercept but not affect the slope significantly.
   On the other hand, increasing the variance should exacerbate the attenuation bias, so in the second regression the slope coefficient should go even closer to zero.
   Indeed this is what we see in the regression outputs.

	Distribution of measurement error		
	N(0,2)	N(0.5,2)	N(0,3)
slope	.1706 (.0041)	.1773 (.0041)	.0852 (.0030)
intercept	.0012 (.0091)	-.0918 (.0093)	-.0011 (.0095)

h. Yes, our estimates reflect this. The two estimated coefficients are very close (we can formally test whether they are statistically different using the test described in (d)—they are not) and the second one has much larger standard error. Since what we did satisfied all the assumptions made in class, this is what we expected.

Dependent variable	readingscore	readingscore_error
slope	.8779 (.0047)	.8646 (.0204)

2.

2.1. The paper presents evidence that textbook funding significantly improves student performance in math and reading in elementary schools. According to the author's preferred specification, a one-time 96.90$ increase in funding per student increases school-level mean test scores by 0.15 school-level standard deviations. Based on these estimates, textbook funding is an intervention with a very high benefit-per-dollar ratio. For middle and high schools, no significant effect is found, but these estimates are less precise.

The question is novel. The effect of textbooks on achievement is understudied. There is virtually no data on the availability of textbooks in schools, and even if there was, it would be difficult to identify the causal impact from observational data.

The main general endogeneity concern is that textbook shortages are probably correlated with the socio-economic status of the local population, quality of the school etc. Even if we have some data to control for such factors, we could probably not remove omitted variable bias completely, so we could not measure the effect of textbooks precisely.

The author proposes to overcome these problems by using a regression discontinuity design (RD or RDD). The main idea of this identification strategy is that schools on the two sides of the cutoff are very similar in every respect other than the policy, so we can use outcomes of schools just above the cutoff as counterfactuals for schools just below the cutoff. Using experimental language (this is a quasi-experiment), we can think of schools just below the cutoff as a treatment group and schools just above the cutoff as a control group.

This is a sharp RDD. Funding was determined as a deterministic function of 2003 API score and these rules were enforced very strictly. (There was a single school that did not receive funding according to the schedule, and based on Figure 3 Panel A, it is outside the bandwidths used for the estimation.)

2.2. See do-file.

2.3. RDD relies on two assumptions: A1) No difference in the outcome for those close to the cutoff in the absence of treatment, and A2) No sorting based on anticipated gains from treatment near the cutoff (see lecture notes).

Failure of A1 means that we expect to see that covariates are not smooth around the cutoff, there are jumps in predetermined characteristics.

Failure of A2 means that we expect to see bunching around the cutoff (in this case school would bunch below the API-cutoff to receive funding). If schools just above the cutoff actively influenced their 2003 API score to receive additional textbook funding we would see more schools just below the cutoff and less schools just above the cutoff. The author argues that this is not the case using institutional details. The bill that introduced the cutoff was proposed on August 24, 2004, and API scores were determined from tests taken in the spring of 2003.

Fiscal substitution: The author has only textbook funding data, but no school-level data on textbook spending or stock. Schools might reallocate some funds on other inputs once they receive additional, earmarked textbook funding, which means that attributing all of the improvement to textbooks is wrong. This could be addressed if we could disaggregate school district-level spending data to the school level, and then see if there is a jump in spending on textbooks and other inputs around the cutoff.

Teacher composition: While the author shows that the number of hours worked by teacher and staff if not affected, there are no discontinuities around the cutoff, teacher composition (as well as staff composition) might be affected. With data on teacher and staff characteristics we can shed some light on the likelihood of this scenario.

Student sorting: In the upcoming academic year students might choose to enroll in the schools that receive funding. This might be addressed by having data on student composition and enrollment. Note that this is a worry only if school enrollment happens after August 24, 2004. If school enrollment occurs before then student composition is not problematic. Knowledge of institutional details is key to rule out this potential explanation of the findings.