FLS 6415: Replication 4 - Instrumental Variables

April 2019

To be submitted (code + answers) by midnight, Wednesday 1st May.

First read the paper by Albertson and Lawrence (2009) on the course website.

The replication data is in the file *IV.csv*, and the important variables are described below. The rest of the variables in the data are just control variables for use in Q10. We are only going to replicate 'Study 2' of the paper (details from page 290), where the research question is whether watching a TV program on affirmative action increased knowledge of and support for a proposition to *eliminate* affirmative action policies.

Table 1: Important Variables

Variable	Description
Watched_Program	The respondent actually watched the TV program
Encouraged_to_Watch	The respondent was encouraged to watch the TV program during the phone call
Info_Proposition	The respondent's self-assessment of whether they are well-informed about the Proposition

1. What is the treatment? What is the control? What is the outcome? What is the instrument for treatment?

The treatment is watching the program on the Proposition. Control is not watching the program. The outcome is the respondent's self-assessment of their knowledge about the Proposition. The instrument is receiving a phone call encouraging you to watch the program.

2. If we did not know about instrumental variables, the basic *observational* regression we might run is to examine directly how the treatment variable is related to the outcome variable. Run this basic observational regression and interpret the results. *NB:* (The outcome variable is an ordered categorical variable - feel free to use either an ordered multinomial logit model or a simple linear OLS regression for all the questions, it doesn't make much difference to the results).

```
d <- read_csv("IV.csv")

d %>% lm(Info_Proposition ~ Watched_Program, data = .) %>% stargazer(header = F,
    keep.stat = c("n"), title = "Q2")
```

Table 2: Q2

	Dependent variable:
	Info_Proposition
Watched_Program	0.296***
	(0.084)
Constant	3.157***
	(0.043)
Observations	498
Note:	*p<0.1; **p<0.05; ***p<0.01

In the observational regression, watching the program is associated with an increase of 0.296 on the information score, which is statistically significant at the 1% level.

3. Do you trust the treatment effect estimates from Q2? What are the major threats to causal inference here? Provide concrete examples of why the estimate in Q2 might be wrong.

No, this is not an accurate estimate of the treatment effect. There may be reverse causation - people with more information about the proposition are more likely to watch the program. There may be omitted variables, eg. people who are more educated or interested in politics are more likely to both have information and watch the program.

4. To conduct an Instrumental Variables analysis, we first need to make sure we have a strong 'first stage', i.e. that our instrument (encouragement to watch the program in the phone call) predicts our treatment variable (watching the program). Using a simple regression, what is the evidence about the strength of our first stage?

```r
d %>% lm(Watched_Program ~ Encouraged_to_Watch, data = .) %>% stargazer(header = F,
    title = "Q4")
```

Table 3: Q4

	Dependent variable:
	Watched_Program
Encouraged_to_Watch	0.407***
	(0.034)
Constant	0.044*
	(0.024)
Observations	507
R^2	0.220
Adjusted R^2	0.218
Residual Std. Error	0.384 (df = 505)
F Statistic	142.219*** (df = 1; 505)
Note:	*p<0.1; **p<0.05; ***p<0.01

The first stage exhibits strong evidence that the instrument is correlated with treatment: the coefficient is substantively large and statistically significant. The F-statistic is 142, well above the benchmark of 10.

5. Now let's perform the 2-Stage Least Squares instrumental variables methodology. First, save the fitted values of the first stage regression from Q4 as another column in your data.

```r
d <- d %>% mutate(first_stage = lm(Watched_Program ~ Encouraged_to_Watch, data = .)$fitted.values)
```

6. Next, run the second-stage regression of the outcome variable on those fitted values from Q5. Carefully interpret the Instrumental Variables regression result.

```r
d %>% lm(Info_Proposition ~ first_stage, data = .) %>% stargazer(header = F,
    keep.stat = c("n"), title = "Q6")
```

The instrumental variables regression estimates that the effect of watching the program is a 0.238 increase in the information measure about the Proposition for people who watched the program because of the phone call. However, this estimate is not statistically significant. Therefore the evidence is very different from that presented by the naive observational regression.

7. The only disadvantage of the 2-Stage Least Squares approach is that it doesn't correctly estimate the standard errors for our estimated treatment effect. Conduct the equivalent all-

Table 4: Q6

	Dependent variable:
	Info_Proposition
first_stage	0.238
	(0.183)
Constant	3.173***
	(0.059)
Observations	498
Note:	*p<0.1; **p<0.05; ***p<0.01

in-one IV approach to the previous analysis using *ivreg* in the *AER* library in R or *ivreg2* in Stata.

```
d %>% ivreg(Info_Proposition ~ Watched_Program | Encouraged_to_Watch, data = .) %>%
    stargazer(header = F, keep.stat = c("n"), title = "Q7")
```

Table 5: Q7

	Dependent variable:
	Info_Proposition
Watched_Program	0.232
	(0.176)
Constant	3.173***
	(0.058)
Observations	498
Note:	*p<0.1; **p<0.05; ***p<0.01

The all-in-one IV strategy more efficiently estimates the standard errors, reducing the uncertainty around our treatment effect.

8. A crucial assumption for the instrumental variables regression is the *exclusion restriction*: that the instrument ONLY affects the outcome through the treatment, and not through any other mechanism. We have to support this assumption by theory and supportive qualitative evidence as it cannot be empirically verified. Make the argument that the encouragement to watch the program through the phone call ONLY affects participants' information about the proposition through its affect on watching the program.

The exclusion restriction explicitly mentioned the TV program and did not mention any alternatives, so it is likely to work through this channel only. It also did not mention the proposition itself.

9. Now pretend you are a reviewer/critic and make the argument that the exclusion restriction assumption is likely to be *false*.

There are many ways that the phone call could lead people to raise their self-evaluation of their information about the Proposition that have nothing to do with watching the TV program. Most obviously, they might become interested in the topic because of the phone call and search for information on the proposition on the internet. This is particularly likely since people knew they would be called again later, and so may have wanted to avoid appearing uninformed. Or it may be simply that the phone call makes them feel ‘special’ or more knowledgable simply for having been in contact about the topic, raising their self-evaluation.

10. The authors’ analysis in Table 4 is more complicated than ours only because it includes control variables in an attempt to make sure the instrument satisfies the exclusion restriction. Add the control variables to *both* the first and second stage 2SLS methodology regressions and interpret the results (it will be slightly different from the values in Table 4).

```
d <- d %>% mutate(first_stage = lm(Watched_Program ~ Encouraged_to_Watch + partyid +
    pnintst + watchnat + readnews + gender + educad + income + white, data = .)$fitted.values)

d %>% lm(Info_Proposition ~ first_stage + partyid + pnintst + watchnat + readnews +
    gender + educad + income + white, data = .) %>% stargazer(header = F, keep.stat = c("n"),
    title = "Q10")
```

Table 6: Q10

	Dependent variable:
	Info_Proposition
first_stage	0.277*
	(0.162)
partyid	−0.017
	(0.016)
pnintst	0.251***
	(0.048)
watchnat	0.0003
	(0.024)
readnews	0.107***
	(0.019)
gender	−0.053
	(0.069)
educad	0.003
	(0.013)
income	−0.008
	(0.013)
white	0.069
	(0.086)
Constant	1.797***
	(0.236)
Observations	498
Note:	*p<0.1; **p<0.05; ***p<0.01

Now the estimated treatment effect is an increase of 0.27 on the self-reported information measure, which is just significant at the 5% level, controlling for the other variables in the regression, and for people who watched the program because of the phone call. We also need to assume no defiers, i.e. that nobody refused to watch the program because they received the phone call.

11. To what group of people ('population') does our estimate of the causal effect of treatment apply? How generalizable would our results be?

Our estimate applies only to those people who were induced to watch the program because of the phone call, and not the always-takers (who were self-motivated to watch the program) or never-takers (who ignored the phone call). This may be a very small group of people, so the generalizability of our results is limited, and we can say nothing about the impact of the program on many of the people who actually watched it, i.e. the always-takers.

More generally, the results cannot be generalized to other types of TV programs, other substantive policy topics, other countries, other demographic groups, or other periods of time further away from elections.