### **GV300** - Quantitative Political Analysis

University of Essex - Department of Government

Lorenzo Crippa Week 16 – 13 January, 2020

#### Communication

For the spring term, new office hour:

Monday 14:00 to 16:00 (before class) Office 5B.153

### Midterm exam - Question 4 (a)

Create a 1000 observation dataset. Generate variables RootCause and OtherThing as independent, uncorrelated variables each drawn from a normal distribution with mean 0 and variance 1.

Create a set of normal error terms with mean 0 and variance 1. Let Outcome = 1 + RootCause + 3 \* OtherThing + errors.

Draw a graphical representation of the data generating process (DGP) involving the variables Outcome, RootCause, and OtherThing.

Draw a graphical representation of the data generating process (DGP) involving the variables Outcome, RootCause, and OtherThing. Are RootCause and OtherThing independent?

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Regress Outcome on RootCause. Report and interpret the result.

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Regress Outcome on RootCause and OtherThing. Report and interpret the result. Did you estimate the causal effect of RootCause on Outcome? Why?

# Question 4 - (a) ii. and iii. results

	Dependent variable: Outcome	
	(ii.)	(iii.)
RootCause	0.860***	0.998***
	(0.102)	(0.033)
OtherThing		3.023***
		(0.033)
Constant	1.079***	1.053***
	(0.101)	(0.033)
Observations	1,000	1,000
$R^2$	0.067	0.901
Adjusted R <sup>2</sup>	0.066	0.901
F Statistic	71.340*** (df = 1; 998)	4,528.766*** (df = 2; 997)
Note:		*p<0.1; **p<0.05; ***p<0.01

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- OtherThing is not a confounder in model ii.: it does not generate an OVB issue.

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- OtherThing is not a confounder in model ii.: it does not generate an OVB issue. The zero conditional mean assumption is met in both cases.

Compare the results of the regressions you ran in 4a.ii and 4a.iii.

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 Model iii. is more precise in its estimate of the causal effect of RootCause, because it models explicitly one factor of the DGP of Outcome (OtherThing), which remains in the error term for model ii.

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- Therefore the estimate of the parameter associated with RootCause is closer to the "true" value in model iii.

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- Therefore the estimate of the parameter associated with RootCause is closer to the "true" value in model iii.
- For the same reason model iii. also performs better in terms of R<sup>2</sup> and F statistics: it explains more variance of the dependent variable.

#### Midterm exam - Question 4 (b)

Create a 1000 observation dataset. Generate variable RootCause following a normal distribution with mean 0 and variance 1. Generate variable OtherThing = 2 \* RootCause + noise where noise follows a normal distribution with mean 0 and variance 1.

Create a set of normal error terms with mean 0 and variance 1. Let Outcome = 1 + RootCause + 3 \* OtherThing + errors.

Draw a graphical representation of the data generating process (DGP) involving the variables Outcome, RootCause, and OtherThing.

Draw a graphical representation of the data generating process (DGP) involving the variables Outcome, RootCause, and OtherThing. Are RootCause and OtherThing independent?

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Regress Outcome on RootCause and OtherThing. Report and interpret the result.

Regress Outcome on RootCause. Report and interpret the result. Did you estimate the causal effect of RootCause on Outcome with this regression? Why?

Regress Outcome on RootCause and OtherThing. Report and interpret the result. Did you estimate the causal effect of RootCause on Outcome? Why?

## Question 4 - (b) ii. and iii. results

	Dependent variable: Outcome	
	(ii.)	(iii.)
RootCause	6.893***	0.994***
	(0.102)	(0.069)
OtherThing		3.003***
		(0.031)
Constant	0.921***	1.009***
	(0.100)	(0.031)
Observations	1,000	1,000
$R^2$	0.820	0.982
Adjusted R <sup>2</sup>	0.820	0.982
F Statistic	$4,540.510^{***} (df = 1; 998)$	$27,733.450^{***} (df = 2; 997)$
Note:		*p<0.1; **p<0.05; ***p<0.01

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 Now only model iii. estimates the unbiased causal effect of RootCause on Outcome. In model ii., indeed, the zero conditional mean assumption is not met, because OtherThing is a confounder which is not explicitly modelled.

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- In model ii.,  $E(errors|RootCause) \neq 0$  because something which is "left" in the error term (that is, OtherThing, which is not modelled) is caused by RootCause.

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- In model ii.,  $E(errors|RootCause) \neq 0$  because something which is "left" in the error term (that is, OtherThing, which is not modelled) is caused by RootCause.
- Omitting OtherThing in model ii. generates an OVB issue, because the variable is a confounder in the DGP.

Compare the results of the regressions you ran in 4b.ii and 4b.iii.

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 Model iii. is correct in its estimate of the causal effect of RootCause (and OtherThing), because it models explicitly all confounders of the DGP of Outcome.

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 Model iii. is correct in its estimate of the causal effect of RootCause (and OtherThing), because it models explicitly all confounders of the DGP of Outcome. Therefore its estimates of the parameters are unbiased.

Compare the results of the regressions you ran in 4b.ii and 4b.iii.

- Model iii. is correct in its estimate of the causal effect of RootCause (and OtherThing), because it models explicitly all confounders of the DGP of Outcome. Therefore its estimates of the parameters are unbiased.
- Model ii. obtains a biased estimate of the causal effect of RootCause on Outcome.

### Question 4 - (b) iv.

Compare the results of the regressions you ran in 4b.ii and 4b.iii.

- Model iii. is correct in its estimate of the causal effect of RootCause (and OtherThing), because it models explicitly all confounders of the DGP of Outcome. Therefore its estimates of the parameters are unbiased.
- Model ii. obtains a biased estimate of the causal effect of RootCause on Outcome. It is larger in absolute value, which makes sense because RootCause enters twice in the DGP of Outcome: directly and indirectly through OtherThing (see causal diagram, point 4b.i)

### Question 4 - (b) iv.

Compare the results of the regressions you ran in 4b.ii and 4b.iii.

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- Model ii. obtains a biased estimate of the causal effect of RootCause on Outcome. It is larger in absolute value, which makes sense because RootCause enters twice in the DGP of Outcome: directly and indirectly through OtherThing (see causal diagram, point 4b.i).
- Notice that the bias of model ii. cannot be inferred by simply looking at statistics such as the  $R^2$  and F statistics.

Load the data set "gb\_recoded.dta". Provide appropriate summary statistics and plots for the variables e5, age, and turnout05.

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Summary statistics in R (from package psych):

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Summary statistics in R (from package psych):

Summary statistics in Stata:

```
1 summarize age gender f1 e5 turnout05
```

#### Summary statistics output (from R):

```
mean
                           sd min max range
                                             se
1
                   47.01
                        15.21
                               18
                                        70 0.32
 data.age
              2301
                                  88
 data.gender* 1732
                   1.51
                        0.50
                               1
                                         1 0.01
 data.f1*
             2301 3.70 3.00 1
                                   9 8 0.06
         2300 2.72 1.49 1
                                   7 6 0.03
5 data.e5*
6 data.turnout05 2301 0.81 0.39
                                         1 0.01
                                0
                                   1
```

#### Summary statistics output (from R):

```
mean
                         sd min max range
                                         se
1
             2301 47.01 15.21
                                     70 0.32
 data.age
                             18
                                88
data.gender* 1732 1.51 0.50 1 2 1 0.01
           2301 3.70 3.00 1 9 8 0.06
4 data.f1*
5 data.e5* 2300 2.72 1.49 1 7 6 0.03
6 data.turnout05 2301 0.81 0.39
                                   1 0.01
                              0
```

\*: these variables are factors. R recognizes them as such.

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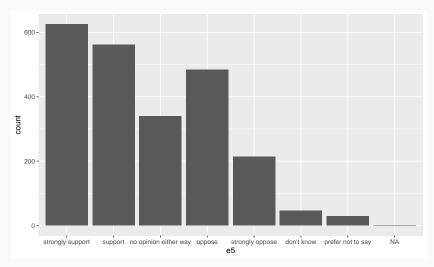
```
1 # e5
ggplot(data, aes(x = e5)) + geom_bar()
3
4 # age
5 ggplot(data, aes(x = age)) + geom_density()
6
7 # turnout05
8 ggplot(data, aes(x = turnout05)) +
  geom_bar(stat = "count")
11 # multivariate
ggplot(data, aes(y = age, x = f1)) + geom_boxplot() +
theme(axis.text.x = element_text(angle = 15))
```

Plots in Stata:

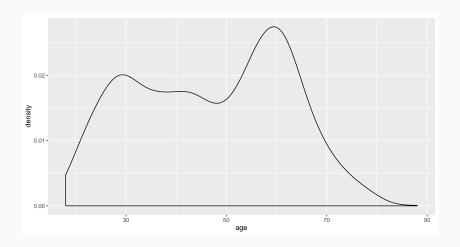
#### Plots in Stata:

```
1 * e5
2 hist e5, discrete xtitle("opinion") xlabel(,
     valuelabel)
3
4 * age
5 kdensity age
6
7 * turnout.05
8 hist turnout05, discrete xlabel(0 1) xtitle("turnout
      2005")
9
10 * multivariate
11 graph box age, over(f1)
```

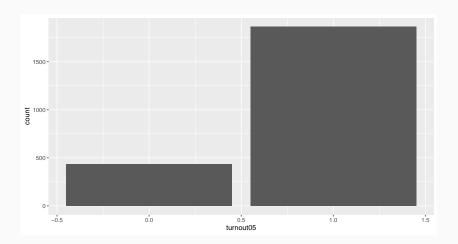
#### Variable e5 (opinion), barplot



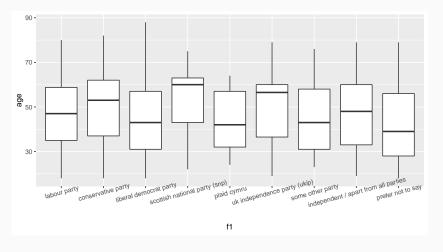
#### Variable age, density



Variable turnout05 (2005 elections turnout), barplot



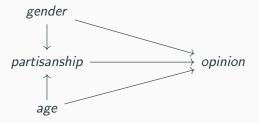
#### Variable age by f1 (partisanship), boxplot



Create a reasonable model of public opinion as a function of the variables given above. Run a linear regression and interpret the outcome of that regression.

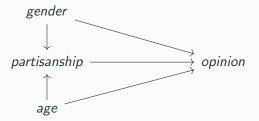
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#### Model:



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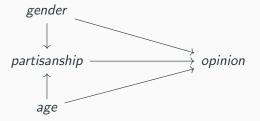
#### Model:



I argue turnout in 2005 elections is not part of the DGP of *opinion*. It does not enter this causal model.

Create a reasonable model of public opinion as a function of the variables given above. Run a linear regression and interpret the outcome of that regression.

Model:



I argue turnout in 2005 elections is not part of the DGP of *opinion*. It does not enter this causal model. Note the confounding variables *age* and *gender*. We *must* model them!

We have factor variables. R treats them automatically as factors. Tell the program to treat them as numeric if you want to.

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#### Model in R:

```
data$e5_num <- as.numeric(data$e5)</pre>
2 data$gender_num <- as.numeric(data$gender)</pre>
3 data$f1_num <- as.numeric(data$f1)</pre>
4
5 # only the dep. variable as non-factor
6 model.f <- lm(e5_num ~ age + gender + f1, data = data)
7
 # all factor variables turned into non-factors
9 model.n <-lm(e5_num ~ age + gender_num + f1_num,</pre>
    data = data
12 # table
stargazer(model.f, model.n, type = "text")
```

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#### Model in Stata:

```
* only the dep. variable as non-factor
2 reg e5 age i.gender i.f1
3 est store model_f
4
5 * all factor variables turned into non-factors
6 reg e5 age gender f1
7 est store model_n
8
9 * table
10 esttab model_f model_n, scalars(N r2 r2_a F p) star(*
     .1 ** .05 *** .01)
```

	Dependent variable: e5_num	
	(1)	(2)
age	-0.019***	-0.020***
	(0.002)	(0.002)
genderfemale	-0.225***	
	(0.069)	
f1conservative party	-0.109	
	(0.091)	
f1liberal democrat party	0.184	
	(0.129)	
f1scottish national party (snp)	0.256	
	(0.254)	
fIplaid cymru	-0.193	
	(0.544)	
fluk independence party (ukip)	-0.004	
	(0.218)	
fisome other party	-0.117	
	(0.208)	
flindependent / apart from all parties	0.038	
	(0.107)	
flprefer not to say	0.373***	
	(0.134)	
gender_num		-0.228***
		(0.069)
f1_num		0.025**
		(0.012)
Constant	3.731***	3.931***
	(0.139)	(0.171)
Observations	1,731	1,731
R <sup>2</sup>	0.055	0.048
Adjusted R <sup>2</sup> F Statistic	0.049 9.990*** (df = 10; 1720)	0.047 29.217*** (df = 3; 1727

	Dependent variable:	
	e5_num	
age	-0.020***	
	(0.002)	
gender_num	-0.228***	
	(0.069)	
f1_num	0.025**	
	(0.012)	
Constant	3.931***	
	(0.171)	
Observations	1,731	
R <sup>2</sup>	0.048	
Adjusted R <sup>2</sup>	0.047	
F Statistic	29.217*** (df = 3; 1727)	
Note:	*p<0.1; **p<0.05; ***p<0.01	

Test the hypothesis: "Age does not have an effect on public opinion about a measure to increase the drinking age."

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First state the null and alternative hypotheses. Our model is:

$$opinion = \beta_0 + \beta_1 age + \beta_2 gender + \beta_3 partisanship + u_i$$

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$$H_0: \beta_1 = 0$$

$$H_1: \beta_1 \neq 0$$

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$$H_1:\beta_1\neq 0$$

The t-statistic will be:  $t = \frac{\hat{\beta}_1 - 0}{S.E.(\hat{\beta}_1)}$ 

If prob. of drawing a t as the one we draw due to sample errors were below conventional levels ( $\alpha = .1$ ,  $\alpha = .05$ ,  $\alpha = .01$ ), we would reject the null.

#### Perform the test (in R):

```
1 se <- sqrt(diag(vcov(model.n)))
2 t.stat <- model.n$coefficients[2] / se[2]
3 t.stat
4
5 pt(t.stat, df = 1730)
6 pnorm(t.stat)</pre>
```

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1 se <- sqrt(diag(vcov(model.n)))
2 t.stat <- model.n$coefficients[2] / se[2]
3 t.stat
4
5 pt(t.stat, df = 1730)
6 pnorm(t.stat)</pre>
```

The t-stat is -8.56 and degrees of freedom are 1730. With these df a t distribution is well approximated by a Z distribution (standard normal).

• The probability of drawing such an extreme t-stat due to sampling errors (p-value) is  $1.23*10^{-17}$ , or  $5.64*10^{-18}$  (from a t and Z distribution respectively).

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- The value of the t-stat is so extreme that it is not even reported on conventional statistical tables.
- To put things in perspective, this means that the probability of drawing this extreme t-stat due to sampling errors is lower than the probability of randomly picking one specific person (say, the one sitting next to you) when drawing from a sample made of all human beings that ever lived (1 in 100 billions:  $prob = 1*10^{-11}$ ). See Kaneda and Haub (2018).

#### Conclusion

All clear? More questions? Thanks and see you next week!

#### References

Kaneda, T. and Haub, C. (2018). How many people have ever lived on earth?

 $\verb|www.prb.org/howmanypeople| have everlived on earth/.$ 

Accessed: 2020-01-11.