Statistical Reasoning Week 11

#### Sciences Po - Louis de Charsonville

Spring 2018

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Research Paper

Paper Improving Bivariate statistics

Regression diagnosis Adjusted R-squared Review of assumptions Diagnosis

Interaction effects

#### Practice

## **Research Paper**

#### Timeline

Final draft 28 April

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#### Describe the Relationship

- If both variables are continuous : look at the correlation using a scatterplot, Pearson's ρ (pwcorr)
- If you can calculate a mean on the DV (continuous or ordinal), and the IV is a dummy or categorical : compare means using bysort bysort and ttest of means;
- If both variables are categorical : look at the percentage distribution with cross-tabulation, and look at Cramer's V for strength;
- Make a lot of graphs (but include only the relevant ones in your paper). "You miss 100% of the plots you don't make"
- Test for significance
  - Look at p-values of each kind of test (ttest, chi2...)

- Cramer's V and Pearson's R are not statistical tests, but tell you the strength of the association;
- Chi-2 and t-tests are statistical tests : they tell you whether the relationship is significant or not;
- pwcorr command with option sig or star provides both : Pearson's ρ and significance of the correlation
- $R^2$  = explanatory power of the predictor variables
- The *p*-values associated to the coefficients in the regression model is about the statistical significance of the predictor.

#### Major requirements

- The entire code should run without errors. Run your entire do-file before submitting.
- Code should be commented and divided in three headings separating 1<sup>st</sup>, 2<sup>nd</sup> drafts and final paper.
- At least one multiple linear regression.
- Name all graphs

#### Minor requirements

- Comment browse and lookfor commands.
- Include your version at the beginning of the code, e.g. version 14. Some commands has changed, like ci, and will generate errors in some versions of Stata.

#### **Required structure**

- 1. Abstract
- 2. Introduction
- 3. Theory and Hypotheseses
- 4. Data and Methods
- 5. Results
- 6. Discussion
- 7. Conclusion
- 8. Appendix
- 9. Bibliography

#### Essential instructions

- Review paper template
- Respect paragraph limits mentioned in the template
- Improve formatting (styles, citations fonts...)

#### 3-step guide

- Rewrite from top to bottom
- Select what you report
- Balance evidence and analysis

- Abstract should communicate your central contribution
- Abstract must be concrete
- Say what you find, not what you look for

#### Example

"Using centuries of Nile flood data, I document that during deviant Nile floods, Egypt's highest-ranking religious authority was less likely to be replaced and relative allocations to religious structures increased. These findings are consistent with historical evidence that Nile shocks increased this authority's political influence by raising the probability he could coordinate a revolt. I find that the available data provide support for this interpretation and weigh against some of the most plausible alternatives. For example, I show that while Nile shocks increased historical references to social unrest, deviant floods did not increase a proxy for popular religiosity. Together, the results suggest an increase in the political power of religious leaders during periods of economic downturn."

Chaney, Eric. 2013. "Revolt on the Nile : Economic Shocks, Religion, and Political Power." Econometrica 81 (5)

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- State clearly the hypothesis you are making
- ► Relate each assumption you make with existing literature
- State every assumption. No undocumented implicit assumption.

- Discuss the results in light of your hypotheses : are they confirmed or not ?
- Weave together theory, hypotheses and results : what are the theoretical implications of your results? Are they in line with theory?
- This is also where you mention the limits of your analysis, the various possible interpretations, the extensions which would be necessary to have more clue to conclude about your research question;

#### Conclusion

Summarize the paper very briefly

Appendix

- Put all tables and graphs with titles;
- Put labels and not variable names in them;
- Multiple linear regression results should be presented in the outreg2 format.

- Both form and content are important;
- Write complete sentences;
- Be clear and concise (put yourself in your reader's shoes);
- State clearly your assumptions
- Be humble
- Proofread

## **Regression diagnosis**

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- Best models are *parsimonious* (unnecessary variables are removed)
- R<sup>2</sup> will always increase when we add more parameters, regardless of whether they are relevant or not
- $R_a^2$  adjusted for the number of parameters is

$$R_a^2 = 1 - \frac{\frac{SSE}{n-p-1}}{\frac{SST}{n-1}}$$
(1)

with n number of observations and p number of variables.

## Adjusted $R^2$

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Example - Add noise to the regression
qui gen noise = uniform()
qui reg lcrime lpolice
estimates store m1
qui reg lcrime lpolice noise
estimates store m2

est table m1 m2, star stats((N r2 r2\_a) b(%7.2f)

Variable	m1	m2			
lpolice	1.18***	1.18***			
noise		0.34			
_cons	2.06***	2.04***			
Ν	97	97			
r2	0.47	0.47			
r2_a	0.47	0.46			
Legend : * p<0.05; ** p<0.01; *** p<0.001					

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Statistical Reasoning

#### Notice that

- The adjusted  $R^2$  decreased
- The parameter for noise is not significant
- None of the other coefficients were affected at all because noise is not correlated to any of them

#### Simple Linear Regression

$$Y = \alpha + \beta X + \epsilon \tag{2}$$

 $\beta$  and  $\alpha$  are correctly estimated under the following assumptions :

- 1.  $H_1$ : Linear in parameters
- 2.  $H_2$  :Random sampling :  $\{Y_i, X_i\}$  are independent and indentically distributed (i.i.d.)
- 3.  $H_3$ : No perfect collinearity : none of the covariates is constant and there are no exact linear relationships among the IVs.
- 4.  $H_4$ : Zero Conditional mean :  $E(\epsilon|X) = 0$  or in *plain English* : "values of the residuals,  $\epsilon$ , does not depend on X.
- 5.  $H_5$ : Heteroscedasticity :  $Var(\epsilon|X) = Var(\epsilon)$ . Variance of the residuals does not depend of X

Gauss-Markov Theorem

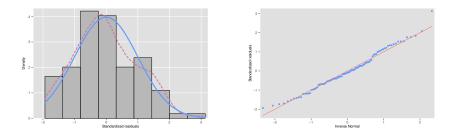
Under assumptions 1-5, the estimates from the linear model are BLUE.

- BLUE : Best Linear Unbiased Estimator
- Best = parameters have the smallest variances amid all linear unbiased estimators

- We use regression diagnostics to check for violations of some assumptions
  - Deviations from the normality assumption
  - Outliers
  - Multicollinearity
  - Heteroskedasticity

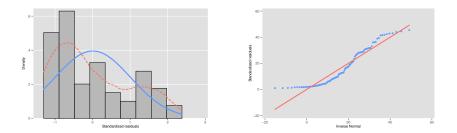
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```
Example 1 - normal residuas
qui gen x = runiform()
qui gen y = x +rnormal(0,0.5)
qui reg y x
qui predict res_std, rstandard
qnorm res_std hist res_std, kdensity norm
```



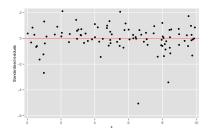
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```
Example 2 - non-normal residuals
qui gen x = runiform()*10
qui gen y = x + 5*x^2 +rnormal(0,0.5)
qui reg y x
qui predict res_std, rstandard
qnorm res_std hist res_std, kdensity norm
```

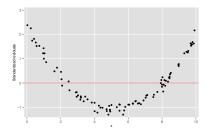


# Plot residuals against X values sc res\_std x yline(0)

#### Normal errors



#### Non-normal errors



- Normality assumption is that the residuals are normally-distributed.
- Normality assumption is not on the unconditionnal dependent variable, Y.
- However, this course requires Y to be normally distributed for correlation tests and an ease of interpretation

#### What is an outlier?

- a value that is larger or smaller than most of the other values of a variable
- Large errors influence results of the linear models
- Large is subjective

## Measures of influence - Cook's distance

► Cook'distance for observation *i*  
$$C_i = \frac{\sum_{j=1}^{n} (\hat{y}_j - y_{\hat{j}(i)})^2}{\hat{\sigma}^2(p+1)}$$

(3)

•  $y_{j(i)}$  is the predicted y when observation i has been removed

#### Model

- Data from Woolridge (cross-sectional firm data on R&D)
- R&D, measured as a percentage of sales (rdintens) is explained by sales
- Model :

$$rdintens = \alpha + \beta sales + \epsilon_i$$

Compute Cook's distance
reg rdintens sales
predict rdintens\_cook if e(sample), cooksd
gen id = \_n
gsort rdintens\_cook
list id rdintens sales rdintens\_cook in 1/5

(4)

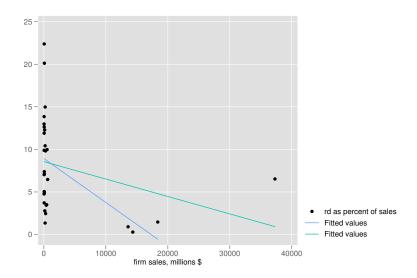
			tens_cook in 1/5
id	rdintens	sales	
1.   2	6.525412	37285	3.172364
2.   19	22.38267	55.4	.1364463
3.   14	20.11834	84.5	.0952832
4.  5	.2858059	14345.4	.0616577
5.   20	.9149596	13585.3	.0458502
+			+

• Observation 2 is more influential than any other.

#### . reg rdintens sales

+-	SS					
	77.6682236			F(1, 27)		
Residual	804.854368					
	882.522592					
Iotal	002.022092	20	31.510004	ROOT MSE	-	5.4598
rdintens	Coef.	Std. Err.	t H	P> t  [95% Con	nf.	Interval]
sales	0002047	.0001268	-1.61 (	0.1180004649	Э	.0000555
_cons	8.562179	1.084104	7.90 (	0.000 6.33778:	1	10.78658
. reg rdintens	sales if id	!= 2				
	SS					
+-				F(1, 26)	=	6.21
+- Model	169.764751	1	169.764751	F(1, 26) Prob > F	=	6.21 0.0194
Model   Residual	169.764751 710.677915	1 _26	169.764751 27.333766	F(1, 26) Prob > F R-squared	=	6.21 0.0194 0.1928
 Model   Residual   +	169.764751 710.677915	1 26	169.764751 27.333766	F(1, 26) Prob > F R-squared Adj R-squared	=	6.21 0.0194 0.1928 0.1618
 Model   Residual   +	169.764751 710.677915	1 26	169.764751 27.333766	F(1, 26) Prob > F R-squared Adj R-squared	=	6.21 0.0194 0.1928 0.1618
 Model   Residual   +	169.764751 710.677915	1 26	169.764751 27.333766	F(1, 26) Prob > F R-squared Adj R-squared	=	6.21 0.0194 0.1928 0.1618
++ Model   Residual   + Total	169.764751 710.677915 880.442667	1 26 27	169.764751 27.333766 32.6089877	F(1, 26) Prob > F R-squared Adj R-squared Root MSE	= = = =	6.21 0.0194 0.1928 0.1618 5.2282
Model   Residual   + Total   rdintens	169.764751 710.677915 880.442667 Coef.	1 26  27 Std. Err.	169.764751 27.333766 32.6089877 t F	F(1, 26) Prob > F R-squared Adj R-squared Root MSE P> t  [95% Con	= = = = nf.	6.21 0.0194 0.1928 0.1618 5.2282 Interval]
Model   Residual   Total   rdintens	169.764751 710.677915 880.442667 Coef.	1 26 27 Std. Err.	169.764751 27.333766 32.6089877 t F	F(1, 26) Prob > F R-squared Adj R-squared Root MSE P> t  [95% Con	= = = nf.	6.21 0.0194 0.1928 0.1618 5.2282 Interval]
+ Model   Residual   + Total    rdintens   + sales	169.764751 710.677915 880.442667 Coef.	1 26 27 Std. Err. .000207	169.764751 27.333766 32.6089877 t H	F(1, 26) Prob > F R-squared Adj R-squared Root MSE P> t  [95% Con- 0.019000941]	= = = = nf.	6.21 0.0194 0.1928 0.1618 5.2282 Interval]
+ Model   Residual   	169.764751 710.677915 880.442667 Coef. 0005158 8.923437	1 26 27 Std. Err. .000207 1.056198	169.764751 27.333766 32.6089877 t H -2.49 ( 8.45 (	F(1, 26) Prob > F R-squared Adj R-squared Root MSE P> t  [95% Con	= = = nf. 1	6.21 0.0194 0.1928 0.1618 5.2282 Interval] 0000904 11.09448

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- Understanding the observations that might change results is important
- > The more data you have, the less influential each observation is
- In some cases knowledge about the subject will help you evaluate if a value can be considered an outlier

- Interpreting coefficient of multiple linear models is done "holding other factors into account"
- $wage = \alpha + \beta_1 age\beta_2 educ + \epsilon$
- β<sub>1</sub> is the effect on average wage for an additional year of age, holding education constant
- If age and education are related, if it is not possible to hold education constant when we change the value for age.
- Ex : sample of young people all going to school, an extra year also implies another year of education

## Perfect collinearity

- Perfect collinearity : one variable is a linear combination of other variables
- Estimation is impossible (H<sub>3</sub> is broken)

```
qui gen sales_profits = 1/3*sales + 2/3*profits
reg rd sales profits sales_profits
```

note: sales\_profits omitted because of collinearity

Source	SS	df	MS	Number of obs	=	32
+				F(2, 29)	=	151.50
Model	2981673.87	2	1490836.94	Prob > F	=	0.0000
Residual	285366.68	29	9840.23035	R-squared	=	0.9127
+				Adj R-squared	=	0.9066
Total	3267040.55	31	105388.405	Root MSE	=	99.198
rd				P> t  [95%		
				P> t  [95%		-
sales			1.39	0.1760081		.0428042
profits	. 216847	.1138528	1.90	0.0670160	082	4497022
sales_profits		(omitted)				
cons		20.13859	0.38	0.708 -33.5	571	48,81896

Create a highly correlated variable but no perfectly collinear

#### Stata

```
qui gen profits_noisy = profits + rnormal(0,5)
qui reg rd profits
est sto m1
qui reg rd profits profits_noisy
est sto m2
est table m1 m2, se p stats(N r2 r2_a F)
    Variable
                   m1
                                m2
              .37204849 1.2433652
    profits |
                 .0217702
                            4.1541153
                   0.0000
                                0.7668
                            -.87198564
profits_no~y
                             4.1572454
                                0.8353
       cons |
              15.836122
                             15.515058
                19.546459
                             19.924432
                   0.4242
                                0.4425
          NI
                       32
                                    32
         r2 |
               .90685005
                             .90699115
        r2 a |
                             .90057675
              .90374505
               292.06137
          FL
                             141.39915
```

- Model fit is still good
- Coefficient for *profits* almost multiplied by three
- Standard errors of profits multiplied by 200
- F statistics went down

 One way to diagnose collinearity is to investigate how each explanatory variable in a model is related to all other explanatory variables in the model

#### Variance inflation factor, VIF

- VIF for variable *j* is  $VIF_j = \frac{1}{1-R^2}$
- The R<sup>2</sup> in VIF is obtained by regression X<sub>j</sub> against all other explanatory variables

### Intuitions

- $R^2$  low  $\rightarrow$  VIF close to 1
- $R^2$  hight  $\rightarrow$  VIF will be high
- ► A rule of thumb is that a VIF > 10 provides evidence of collinearity. (R<sup>2</sup> > 0.9)

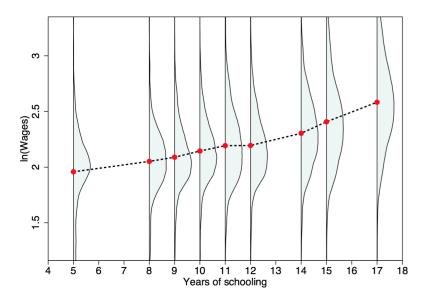
## Signs of collinearity

- Collinearity makes estimation "unstable"
- Large changes in estimated parameters when a variable is added / deleted
- Signs of coefficients do not agree with expectations (require subject knowledge)

### What to do

- Exploratory analysis to detect highly correlated predictors
- Understand what drives multicollinearity
- Easy cases : drop one variable
- ► Harder cases : more data / different type of model

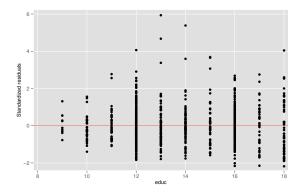
# Heteroskedasticity



#### Example

$$wage = \alpha + \beta_1 educ + \beta_2 age + \epsilon \tag{5}$$

reg wage educ age
predict res\_std, rsta
sc res\_std educ, yline(0)



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hettest

#### Use the Breusch-Pagan test

```
reg wage educ age
estat hettest, rhs
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: educ age
chi2(2) = 41.49
Prob > chi2 = 0.0000
```

- We reject  $H_0$ : there is heteroskedasticity
- We can also test for age and education separately

```
estat hettest age
                                                      estat hettest educ
Breusch-Pagan / Cook-Weisberg test
                                                     Breusch-Pagan / Cook-Weisberg test
                                                     for heteroskedasticity
for heteroskedasticity
         Ho: Constant variance
                                                               Ho: Constant variance
         Variables: age
                                                               Variables: educ
         chi2(1)
                            1.59
                                                               chi2(1)
                                                                                39.70
         Prob > chi2 = 0.2073
                                                               Prob > chi2 = 0.0000
```

Heteroskedasticity comes from education

### ► Use the Huber-White robust s.e. (sandwich estimator)

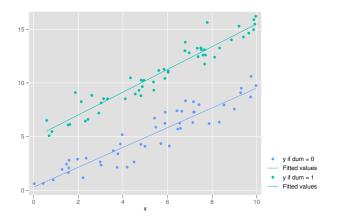
- reg wage educ age, vce(robust)
- Sandwich estimator is asymptotically unbiased : ok with large samples, not with small ones
- Use transformation of the variables, like logs, may help
- OLS estimates are consistent even if there is heteroskedasticity, but the standard errors are not.

# Interaction effects

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# Interaction effects

- Multiple regression : each X<sub>i</sub> has a straight line relationship with the mean of y, holding other varialbes constant
- $y = \alpha + \beta x + \delta d u m + \epsilon$

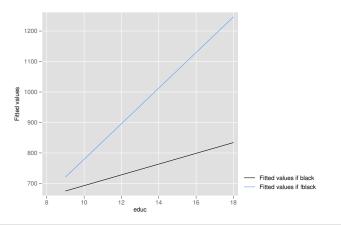


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## Interaction effects

 However, the effect of an explanatory variable may change considerably as the value of another explanatory variable in the model changes

tw (sc wage educ if black) (sc wage educ if !black)



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#### 2 main choices

- Run separate models for each categories
- Include interaction variable

x1#x2

#### Example

#### reg earnings i.race i.sex race#sex

Source   SS	df		Number of obs F(3, 29553)		29,557	
Model   17141.3369 Residual   412226.012	3 5	713.77898	Prob > F	=	0.0000	
++			Adj R-squared		0.0398	
Total   429367.349	29,556 1	4.5272482	Root MSE	=	3.7348	
earnings   +			. t P>			
race   Black and hispanic						
sex   Female   	-1.484246	.0532738	-27.86 0.	000	-1.588665	-1.379827
race#sex   Black and hispanic#Female   	.3844973	.093391	4.12 0.	000	.2014467	.5675478
_cons	4.681477	.0392636	119.23 0.	000	4.604518	4.758435

#### $earnings = \alpha + \beta_r race + \beta_2 sex + \beta_3 racesex + \epsilon$ (6)

#### Interpretations

- $\beta_1$  represents the effect of *race* on *earnings* when *sex* = 0.
- $β_2$  represents the effect of *sex* on *earnings* when *race* = 0.
- $\beta_3 > 0$ : the effect of *race* in earnings increase when *sex* = 1
- ▶  $\beta_3 > 0$ : the effect of *race* in earnings decrease when *sex* = 1

### Keep in mind

- Include both variables alone, not only the interaction variable
- The interpretation of the coefficients of these single variables is different from a common multiple linear regression
- Use margins and marginsplot

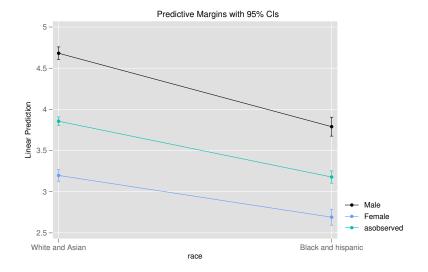
#### margins race sex race#sex

Predictive margins Number of obs = 29,557 Model VCE : OLS

Expression : Linear prediction, predict()

Delta-method										
	Margin	Std. Err.	t	P> t	[95% Conf. Interval]					
+-										
race										
White and Asian	3.855869	.0265465	145.25	0.000	3.803836	3.907901				
Black and hispanic	3.178091	.0378784	83.90	0.000	3.103847	3.252334				
sex										
Male	4.387346	.0326408	134.41	0.000	4.323368	4.451323				
Female	3.029934	.0291434	103.97	0.000	2.972812	3.087056				
race#sex										
White and Asian#Male	4.681477	.0392636	119.23	0.000	4.604518	4.758435				
White and Asian#Female	3.19723	.0360065	88.80	0.000	3.126656	3.267805				
Black and hispanic#Male	3.789823	.0585567	64.72	0.000	3.675049	3.904597				
Black and hispanic#Female	2.690074	.0495469	54.29	0.000	2.59296	2.787188				

# margins race sex race#sex marginsplot





# **Practice** : Satisfaction with Health Services in Britain and France

- Run step by step week11.do
- Remember to comment run setup
- Install packages manually if you are using Sciences Po computer