violations

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outline

misc

intuition

collinearity again

heteroskedasticity

normality of residuals

endogeneity

[*] more diagnostics

[*] elements of research design: causality

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changes from before

- ◇ dropped autocorrelation–assuming you use cross-sec data
  - not time series, not panel

outline

violations

- so far we have just talked about the regressions that satisfy assumptions
- but what happens when assumptions are violated?
  - typically, they are!
- and what you can do about it ?

practical considerations

- you will usually have heteroskedasticity in crosssectional data
- (and autocorrelation in time-series data) [skipped]
- (and both in panel data) [skipped]
- "unobserved heterogeneity" = LOVB
- outliers/leverage
- normality of residuals
- you should *always* test all of them (except autocorr in unclustered cross-sectional data and normality in datasets>1k)
- when you report reg results, it is expected and assumed you took care of all assumptions

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we discussed collinearity earlier

- if perfect, then you cannnot estimate std err
  - stata will just drop a variable
  - with dummies–if you incl all cat–it is so called "dummy trap"
- otherwhise, collinearity does not violate any assumption
- just makes std err bigger
- it is just like "micronumerosity"
- typically, do nothing

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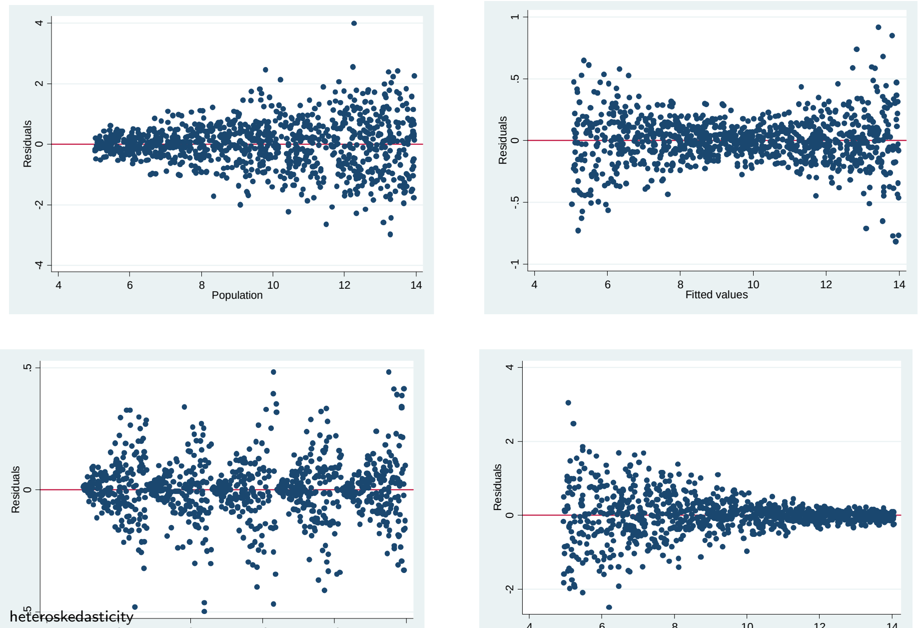
examples



Residuals
Population
Residuals
Fitted values
Residuals
Residuals

violation

- ◇ the variance of Y conditional on X varies from one observation to another
  - eg it may depend on the values of X
- ◇ if true:
  - $\hat{\beta}_j$ still unbiased
  - $s_{\hat{\beta}_j}$ is not as accurate as reported by software
  - not BLUE because not efficient

diagnosis

- eyeball
- test
  - there are many tests... eg Breush-Pagan

solutions

- ◇ calculate robust se
- ◇ transform variables (*if* theoretically justifiable)
  - heteroskedasticity might indicate you are working in the wrong metric
  - a popular transformation that often works is log
  - log is popular for skewed distributions like income...
- ◇ dofile: het

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only worry if you have small sample

- don't have to worry about this at all if sample is big
- if sample is small, after running regress
- can predict residuals `predict resid,r`
- do a histogram and plot them
- if they look very unnormal, don't be too trusting in significance
- try to get more data!

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closely related to design!

- ◇ if you have bad design, you'll have endogeneity
- ◇ curiously, economists are obsessed with it
- ◇ but other fields aren't
- ◇ a superb and readable reference is Sorensen (2012) `http://people.bu.edu/tsimcoe/code/Endog-PDW.pdf`
- ◇ a. gujarati "a note on causality and exogeneity" ed5 p.657, ed4 p.701

what is it

- technically, if x and error term are correlated
- so there is some Z that predicts Y and correlates with X
- see also discussion of Z in previous research resign section
- so it can be just LOVB, or unobserved heterogeneity
- unobserved heterogeneity: see Rumsfeld's unknown unknowns in previous section

simultaneity and self-selection

- ◇ but usually by endogenity we mean bigger problems
- ◇ simultaneity and self-selection
- ◇ and they are bigger problems because no amount of control vars helps
- ◇ simultaneity not only $X \rightarrow Y$ but also $Y \rightarrow X$
- · could do Granger causality or IV
- ◇ but best do an experiment, or natural experiment
- ◇ think deeply about the relationship between X and Y
- ◇ one of the best ways to think deeply, i think, is to use INUS condition

the bottom line

- the bottom line is that in experiment U/As are assigned to levels of X at random
- think about whether that is the case in your study (after controlling for other Xs)
- or at least if that's the case to large degree
- you want to think about selectivity and self-selection early in the process: at the research design stage
- think about **source of variability** in X
- or data generating process as pol sci would put it

outline

Nick's modeldiag

- http://www.stata-journal.com/sjpdf.html?articlenum=gr0009
- dofile:modeldiag

ucla diagnostics

- ◇ http://www.ats.ucla.edu/stat/stata/webbooks/reg/chapter2/statareg2.htm
- ◇ most useful:
  - scatter dfbeta ...
  - lvr2plot, ml()
  - avplot(s)
- ◇ thase are the thing that you should always do in your research

bonus

- ucla scroll to 1.5 transforming variables `http://www.ats.ucla.edu/stat/stata/webbooks/reg/chapter1/statareg1.htm`
- help regress postestimation

outline

research design

- whether you have good or bad research design does not violate assumptions
- but it is critical for ability to argue causality
- causality is acheived with design, not with statistics (incl regression)

research design is a class itself

- research design is about designing your research
- i will just mention few things that will be important for this class
- a quick, useful and applied reference is http://www.socialresearchmethods.net/kb/design.php
- a more in-depth treatment is Lawrence B. Mohr, Impact Analysis for Program Evaluation books.google.com/books?isbn=0803959362
- also see http://knowledge.sagepub.com/view/researchdesign/SAGE.xml
  - guess have to be on campus to access it for free

causality

◇ much of research design is about causality

· want to show X $\rightarrow$ Y

◇ correlation is necessary for causality

· (in rare cases suppressor var makes it unnecessary, eg (Mazur, 2011))

◇ but not sufficient

◇ `http://www.tylervigen.com/`

INUS condition (Mackie, 1980)

- a useful way of thinking about causality: Insufficient but Non-redundant part of Unnecessary but Sufficient Condition
- many, if not most causes are INUS conditions
- eg a cigarette as a cause of forrest fire
  - it's Insufficient, because by itself it is not enough, eg you also need oxygen, dry leaves, etc
  - it is contributing to fire, hence Non-redundant
- and along with other stuff (oxygen, dry leaves etc) it constitutes Unnecessary but Sufficient Condition
  - it's not necessary for fire, it can be lightening, etc
  - but it's sufficient – it's enough to start the fire

basic concepts

- ◇ Y: a dependent variable, outcome
- ◇ X: an independent variable, predictor
- · (T: (treatment), like X)
- ◇ Z: some other variable
- ◇ want to show $X \to Y$ (X affects (causes) Y)
- · and not the other way round ($Y \to X$)
- · and not $Z \to Y$; eg X(CO_2),Y(temp), Z(sun temp)
- · it is difficult to argue !
- · after all, there are unknown unknowns (Z's that we are unaware of)

The Problem: Unknown Unknowns

- there are known knowns; there are things we know that we know
- there are known unknowns; that is to say, there are things that we now know we don't know
- but there are also unknown unknowns–there are things we do not know we don't know
- (Donald Rumsfeld)
- how do we deal with unknown unknowns?
- do an experiment!

The Problem put another way: Counterfactual

- ◇ it all boils down to comparing
  what happened to what would have happened had the treatment not happened
- ◇ eg we got a new teacher and now kids perform better on SAT
  - to know whether the teacher caused better performance we would need to know what would have happened to SAT scores without this teacher (scores might have gone up due to Z),
  - and compare it to what actually happened

The Problem put another way: Counterfactual

- ◇ the problem is that we do not observe counterfactual (we can try to infer it though)
- ◇ counterfactual is the effect of all knowns/unknowns (incl. unknown unknowns)
- ◇ how do we deal with lack of counterfactual
- ◇ do an experiment!
- ◇ (or if you cannot, try to estimate it somehow)

the gold standard [ask IRB appr!]

◇ the experimental design give few examples

◇ only with experimental design you can confidently argue causality

◇ and it is because randomization takes care of the known and unknown predictors of the outcome (draw a picture of 2 groups of people)

· in other words, it establishes a counterfactual

◇ but wait !

· most of the time we cannot have an experimental design because it is unethical and politically impossible
eg we cannot randomly assign kids to bad school or to smoking http://www.socialresearchmethods.net/kb/desexper.php

internal validity

- internal validity is about causality
- you have internal validity if you can claim that X causes Y
  - eg some drug X causes some disease Y to disappear
  - http://knowledge.sagepub.com/view/researchdesign/n43.xml#n43
  - http://knowledge.sagepub.com/view/researchdesign/n192.xml#n192

threats to internal validity

- ◇ history, maturation, regression to the mean
  - something else happened that caused Y
  - things develop over time in a certain way
- ◇ selection bias, self selection
  - does smoking causes cancer ?
  - maybe less healthy people select to smoke ?
- ◇ http://knowledge.sagepub.com/view/researchdesign/n192.xml#n192

spurious correlation

- ◇ you think that X causes Y, but actually it is Z
- ◇ global warming:
  - we have it–we can measure temperature
  - but what's the cause: CO_2 or Sun activity?

reverse causality

- a closely related topic to spurious correlation is reverse causality
- here, instead of some other Z that causes Y instead of X
- we have Y causing X, as opposed to X causing Y...
- what do we do ?

reverse causality

- ◇ you may try to find some other X that measures the same or similar concept and that cannot be caused by Y
- ◇ eg instead of education $\rightarrow$ wage; do father's education$\rightarrow$ wage (your wage can reverse cause your education, but not your father's education)
- ◇ find some exogenous (external) shock: policing$\leftrightarrow$crime
- ◇ but terror attack/alert $\rightarrow$policing$\rightarrow$crime; we know that policing$\rightarrow$crime; not the other way round

- `https://www.law.upenn.edu/fac/jklick/48JLE267.pdf`

natural experiment

- ◇ again most of the time you cannot have an experiment
- ◇ but there are natural experiments or exogenous shocks
- ◇ exogenous meaning that they are caused externally (like an experimenter's randomization) and somewhat randomly (at least with relation to a problem at hand
  - eg earthquake (any weather, eg storm); terrorist attack; policy change (less random)
- ◇ in model simply have dummy for U/As affected storm, policy etc
  - eg get data from `http://www.statepolicyindex.com/` and study state interventions! great data!

causality without experiment?

- ◇ yes! well maybe, but you need to do lots of work...
- ◇ essentially you want to exclude alternative explanations
- ◇ so you act like a devil's advocate...
- ◇ try to abolish your story / find an alt explanation
- ◇ if you cannot find any, then your story is right ...
  - · until disproved
  - · just use regression and "control" for other vars
- ◇ there are some designs that improve our inference greatly over having no design at all (ex post facto, observational)

ex post facto: $X_1 Y_1$

- ◇ very common...it is *no* design
- ◇ non-experimental, cross-sectional, observational, correlational; you'll most likey do this
- ◇ we start investigation "after the fact"
- ◇ no time involved, don't know whether X precedes Y
- ◇ both, X and Y are observed at the same time examples?
- · (but X must precede Y in order to be causal)
- ◇ practically impossible to argue causality here
- ◇ but cheap and big N, and good external validity

ex post facto: $X_1 Y_1$

- useful, many “causes” were discovered using observational studies
- eg smoking→cancer was found out using ex post facto
- and then confirm using better designs
- `http://knowledge.sagepub.com/view/researchdesign/n145.xml`
- `http://knowledge.sagepub.com/view/researchdesign/n271.xml#n271`

(2 group) comparative change: $\frac{Y_{E1} X_2 Y_{E3}}{Y_{C1} \quad Y_{C3}}$

- ◇ eg H_0 : police with better guns fights crime better
- ◇ measured crime rate in 2010 in Camden (Y_{E1}) and Newark (Y_{C1})
  - · in 2011 give super guns to police in Camden (X_2), (but not in Newark)
  - · in 2012 measured crime rate Camden (Y_{E3}) and Newark (Y_{C3})
- ◇ if crime rate dropped more in Camden than in Newark, then we have evidence that the guns worked
- ◇ stata: see so called DID `http://www.princeton.edu/~otorres/DID101.pdf`

MACKIE, J. (1980): The cement of the universe, Clarendon Press Oxford.

MAZUR, A. (2011): "Does increasing energy or electricity consumption improve quality of life in industrial nations?" Energy Policy, 39, 2568–2572.

SORENSEN, J. B. (2012): "Endogeneity is a fancy word for a simple problem," Unpublished.