violations

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outline

intuition

collinearity again

heteroskedasticity

normality of residuals

[*] more diagnostics

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violations

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

violations in practice

- 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 perfectly collinear var
  - 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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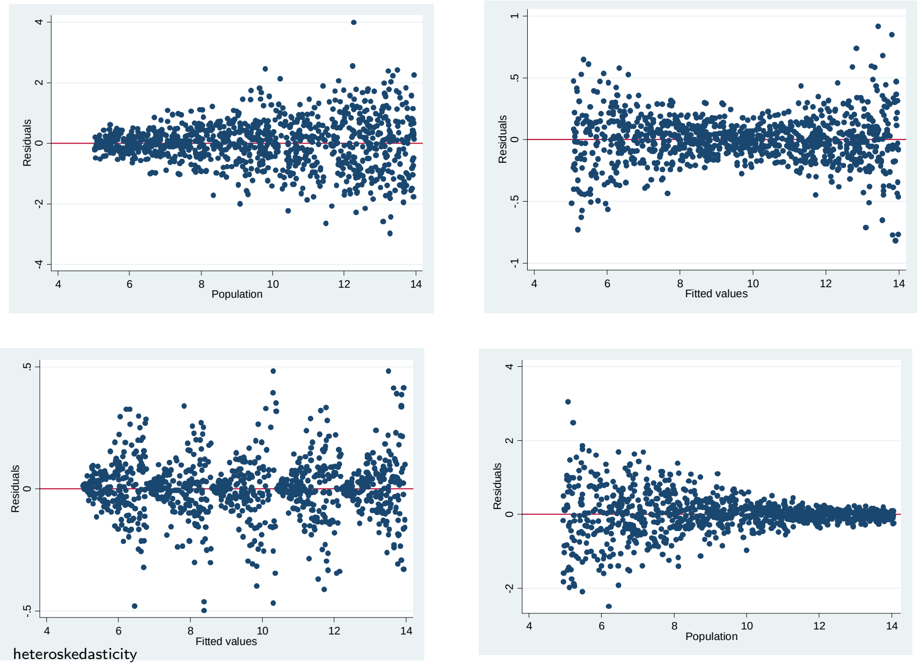
examples


Residuals
Population
Residuals
Fitted values
Residuals
Fitted values
Residuals
Population

violation

- heteroskedascity=pattern in residuals
- 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

diag + solution

- test eg Breush-Pagan
- 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
  - eg log is popular for skewed $ amounts 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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Nick's modeldiag

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

ucla diagnostics

- https://stats.idre.ucla.edu/stata/webbooks/reg/chapter2/stata-webbooksregressionwith-statachapter-2-regression-d
- most useful:
  - scatter dfbeta ...
  - lvr2plot, ml()
  - avplot(s)
- you should always do these in your research
- may also want to transform variables if needed: 1.5 transforming variables https://stats.idre.ucla.edu/stata/webbooks/reg/chapter1/regressionwith-statachapter-1-simple-and-multiple-regres
- and see help regress postestimation

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