Advanced Quantitative Research Methodology, Lecture Notes: Robust Standard Errors[1]

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March 9, 2015

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- Are: A good test for misspecification

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- A better use for RSEs: as a test for misspecification

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Still allows for heteroskedasticity

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Standard linear-normal regression model assumptions

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  - The idea generalizes to any MLE model

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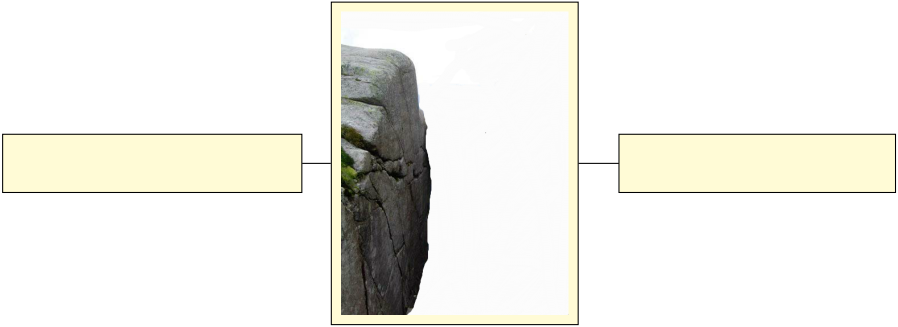

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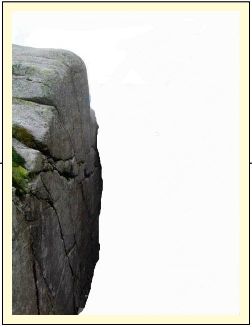
Model Misspecified



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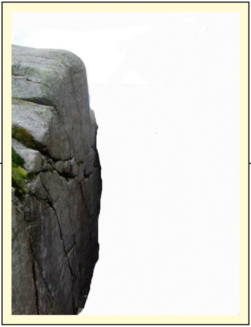
Model Misspecified

(point estimates biased)



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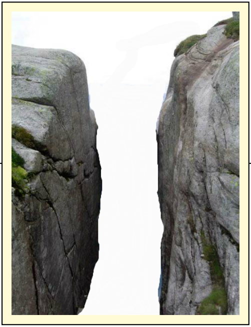

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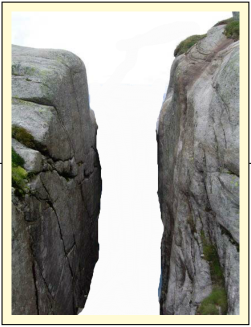

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Goldilocks Region

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Goldilocks Region

but not so much as to bias everything else

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- Parts of the model are wrong; why do we think the rest is right?
- If SE$\neq$RSE: find missspecification, fix model, rerun until SE$=$RSE

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- Robust SE (0.34) $\approx$ classical SE (0.32)

Transformation of Y: Becomes Normal

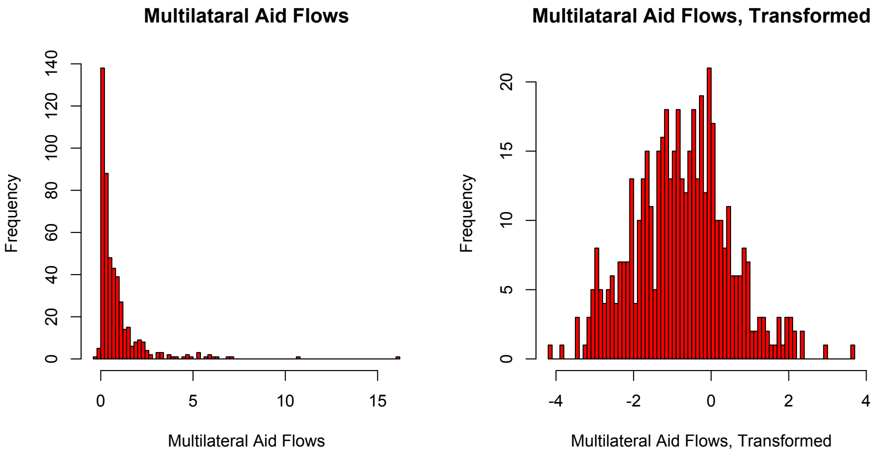
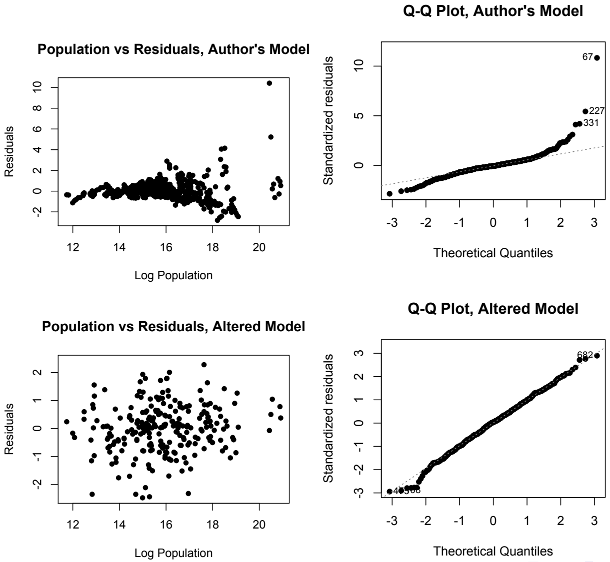


Figure: Distribution of the dependent variable before (left) and after (right) the Box-Cox transformation.

Transformation of Y: Removes Heteroskedasticty



Results: Transformed Model, Opposite Results

The misspecification $\rightsquigarrow$ bias, not inefficiency