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

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Overview of Robust SEs

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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

For RSEs to help: Everything has to be Juuuussttt Right

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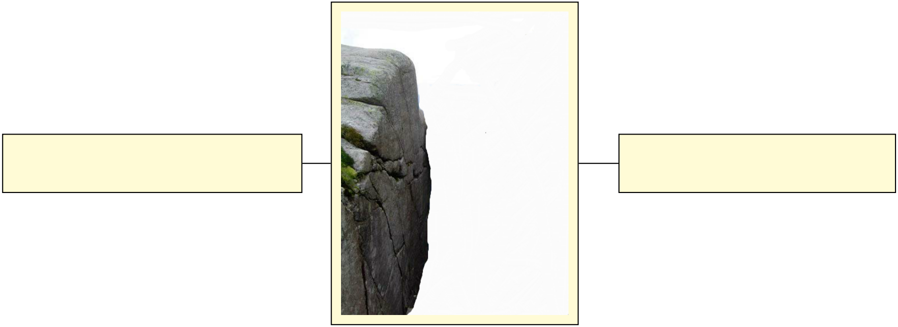

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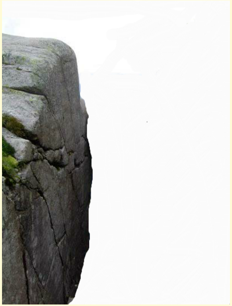
Model Misspecified



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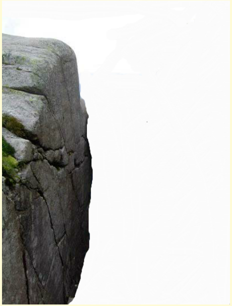
Model Misspecified

(point estimates biased)



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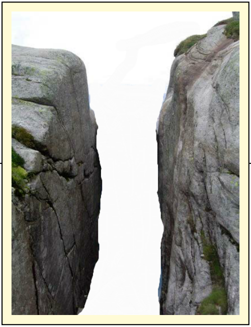

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Goldilocks Region

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Goldilocks Region

but not so much as to bias everything else

Model Misspecified

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Model Correct

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- If SE$\neq$RSE: find missspecification, fix model, rerun until SE$=$RSE