

Advanced Quantitative Research Methodology, Lecture Notes: **Single Equation Models**¹

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March 23, 2014

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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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Variance matrix unconstrained (includes covariances)

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Still allows for heteroskedasticity

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Standard linear-normal regression model assumptions

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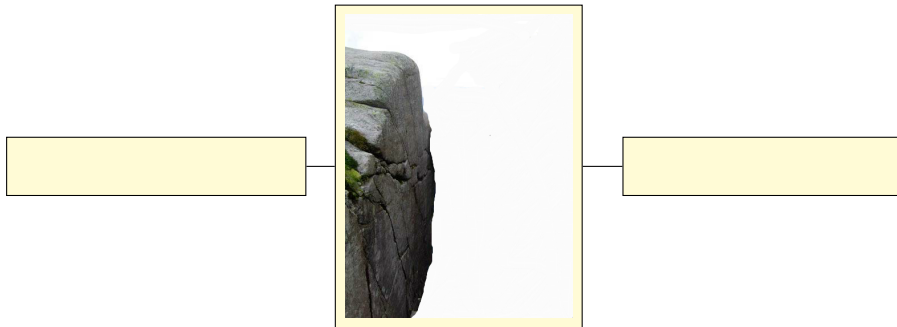
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 - The idea generalizes to any MLE model

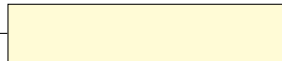
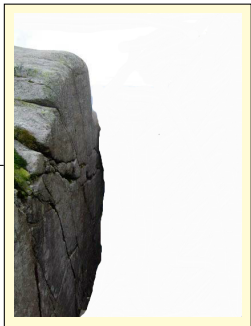
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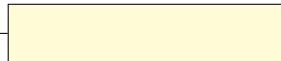
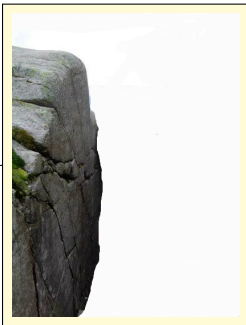
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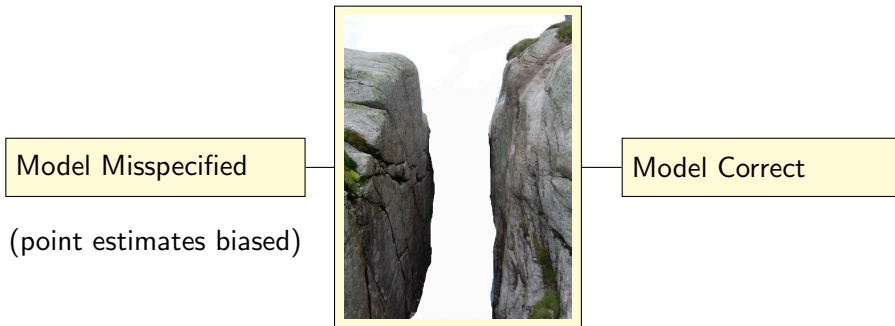
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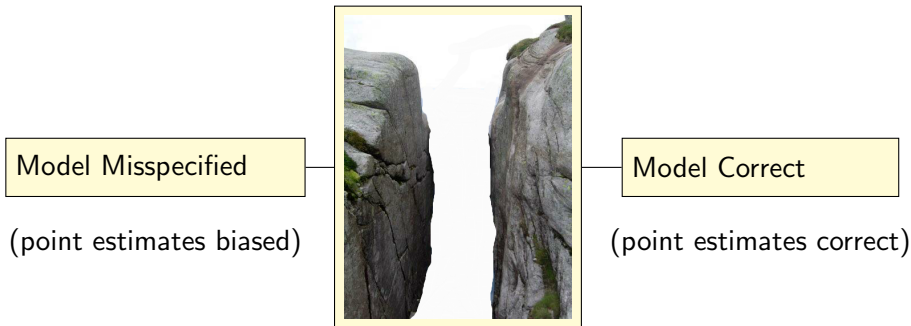
(point estimates biased)



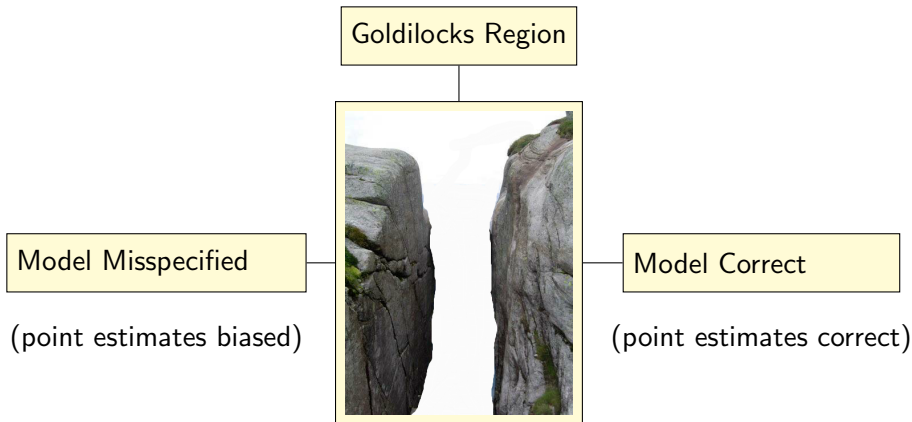
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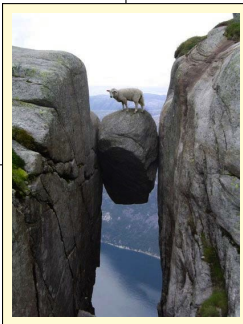


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Goldilocks Region



Model Misspecified

(point estimates biased)

Model Correct

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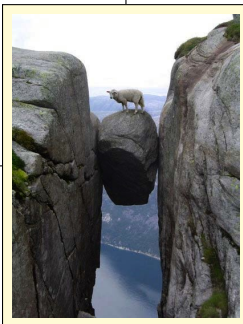
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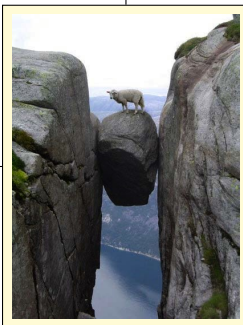
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- Parts of the model are wrong; why do we think the rest is right?
- If $SE \neq RSE$: find misspecification, fix model, rerun until $SE = RSE$