

Advanced Quantitative Research Methodology, Lecture

Notes: Robust Standard Errors¹

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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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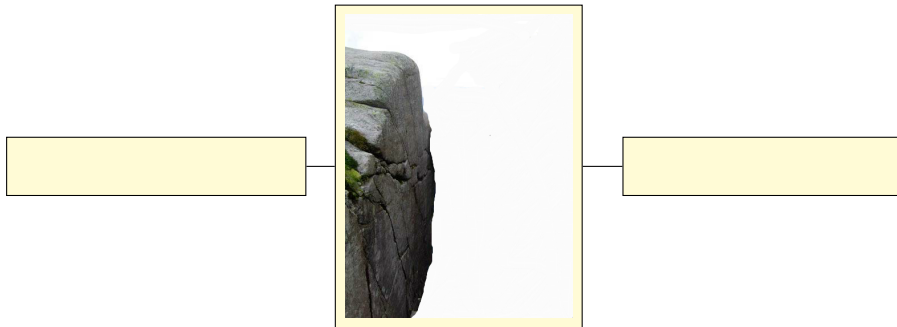
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 - The idea generalizes to any MLE model

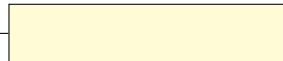
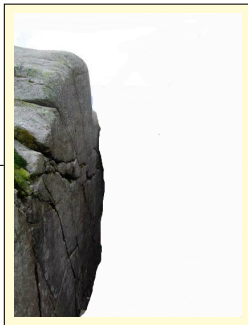
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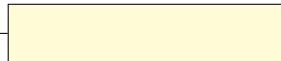
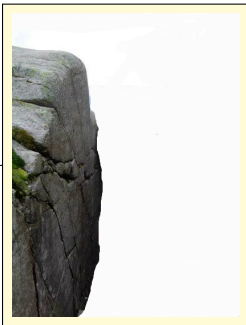
Model Misspecified



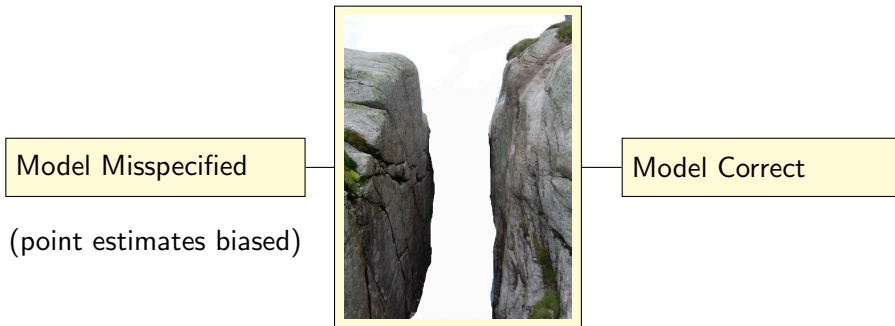
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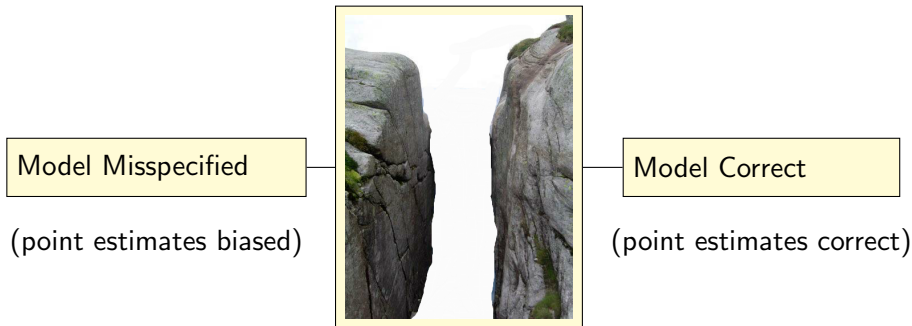
(point estimates biased)



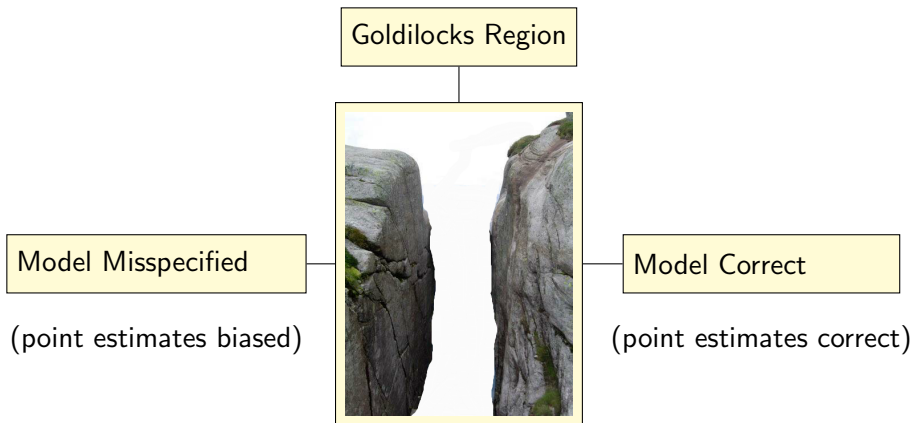
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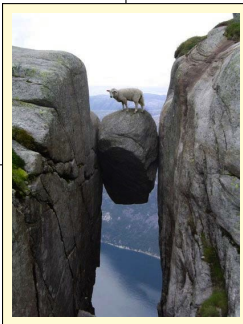


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Goldilocks Region



Model Misspecified

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Model Correct

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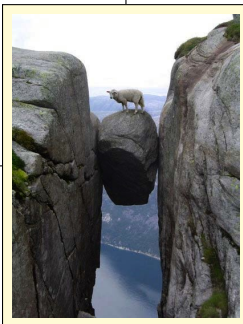
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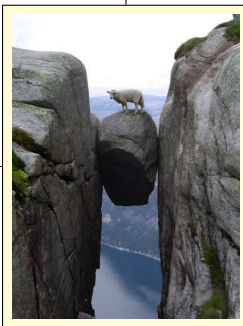
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 - We don't know: the substantive meaning of our results. How big are they, really?
 - We can't check: whether model implications are realistic.
- Parts of the model are wrong; why do we think the rest is right?
- If $SE \neq RSE$: find misspecification, fix model, rerun until $SE = RSE$