- Jonathan Dushoff, McMaster University

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Tessa Wessels, Faces on a Train

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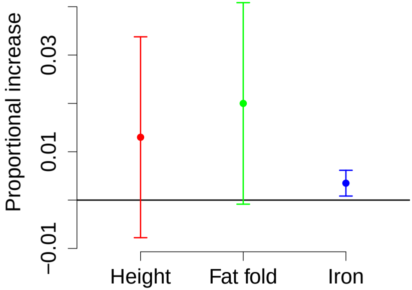

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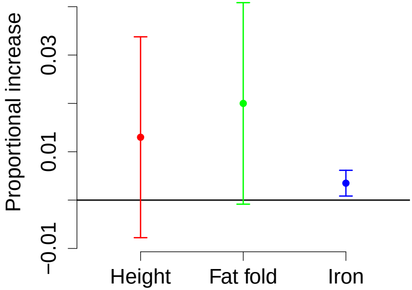

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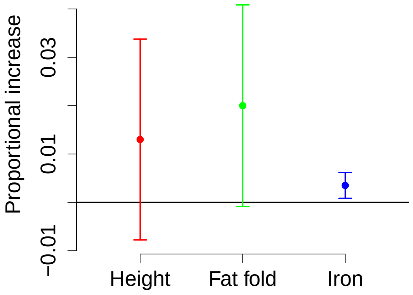

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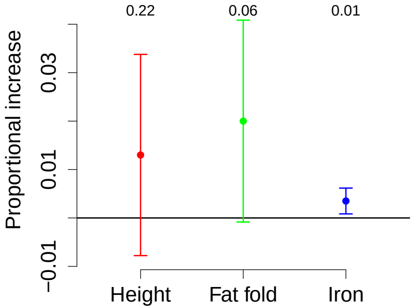

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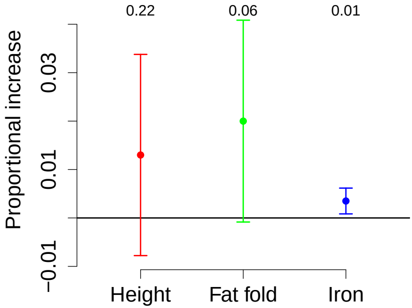

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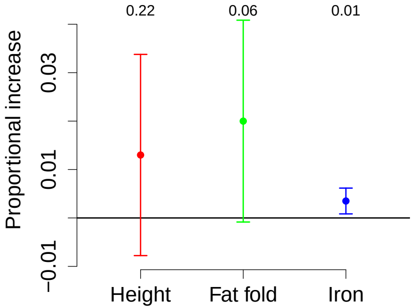

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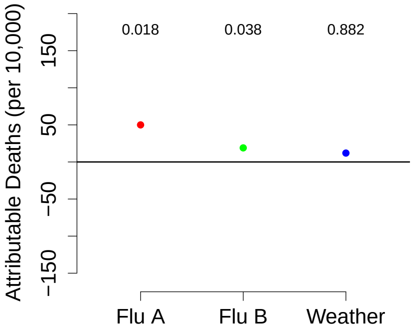

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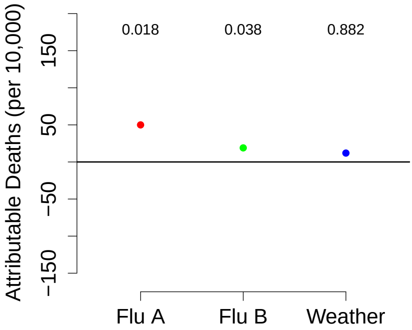

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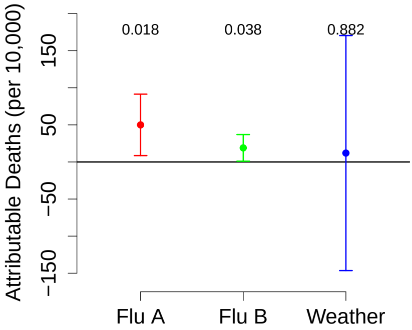

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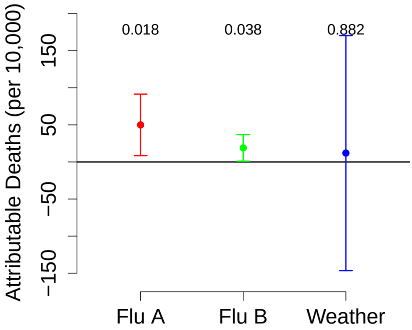

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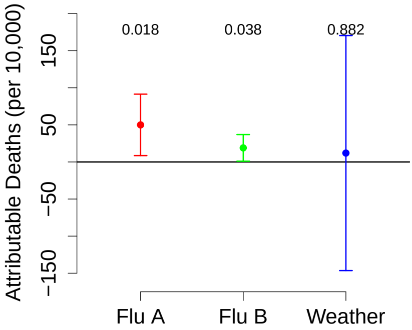

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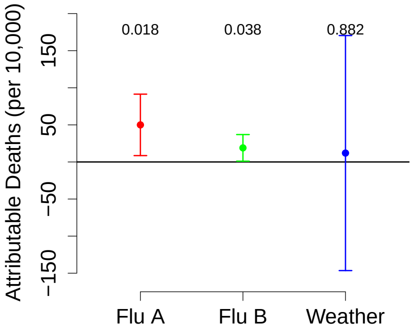

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Flu masks


WARNING
This respirator helps protect
against certain particles.
Misuse may result in sickness
or death. For proper use, see
supervisor or box or call 3M
1-800-247-3941. NIOSH
N95
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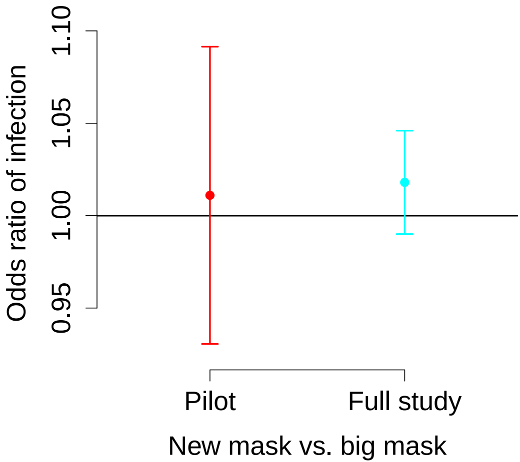
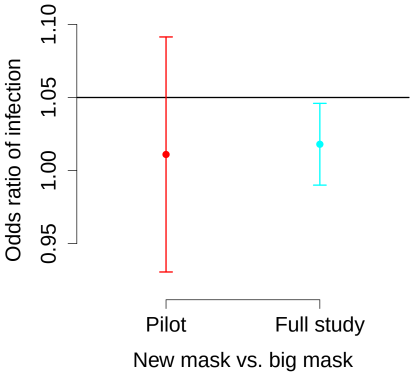


Non-inferiority trial



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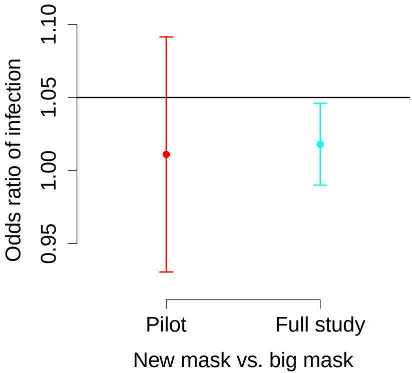

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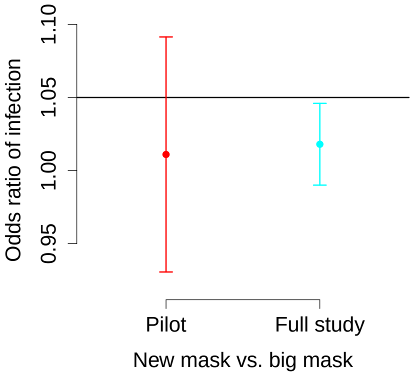

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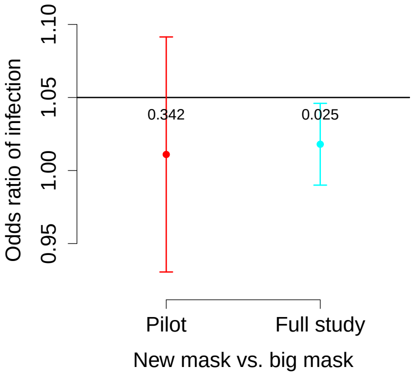

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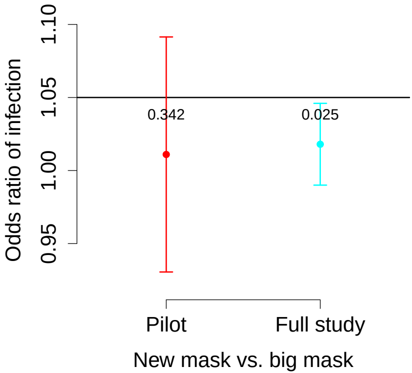

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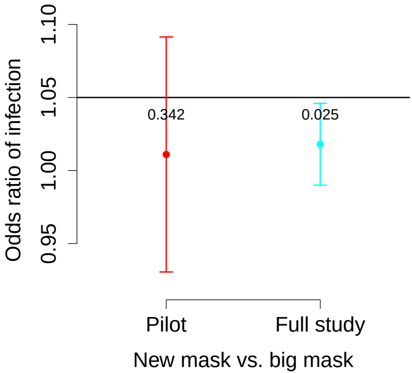

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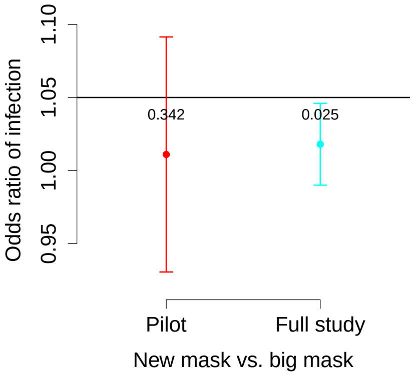

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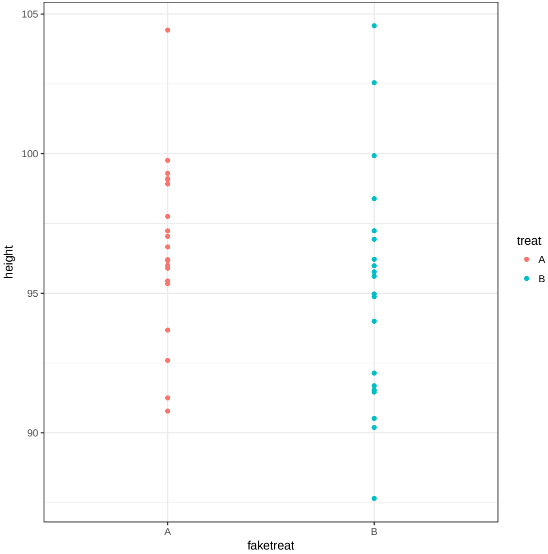
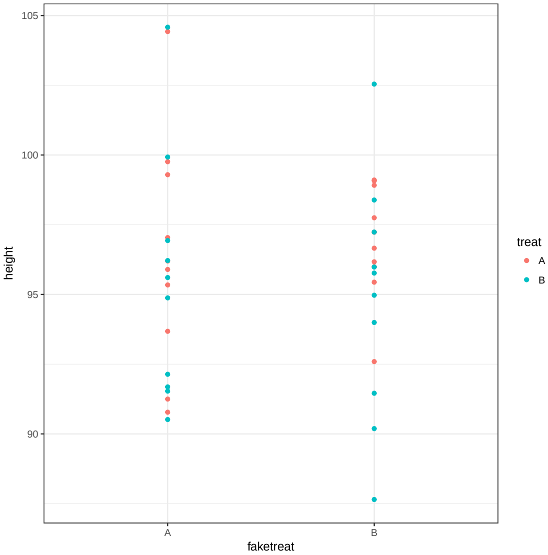
Height measurements



Scrambled measurements



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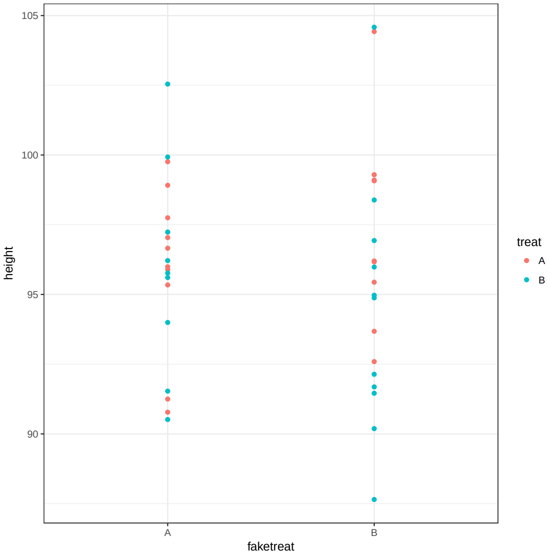

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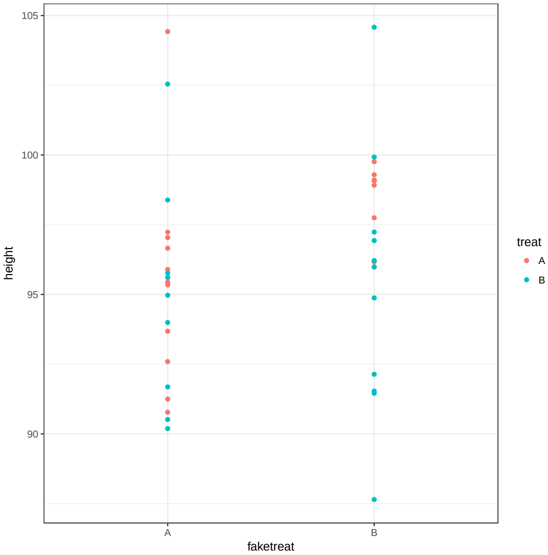

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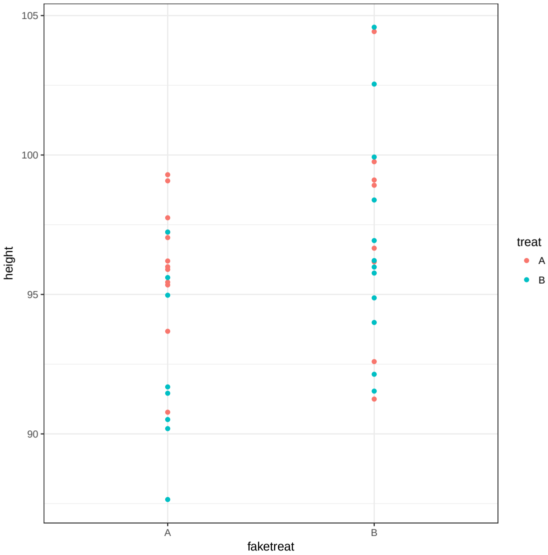
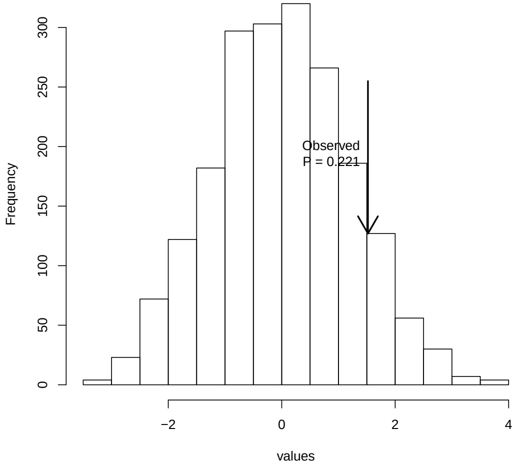


The null distribution



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Vitamin A study

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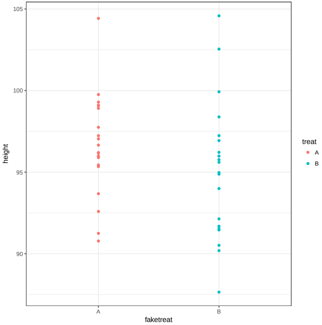

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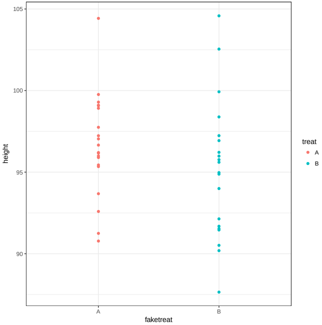

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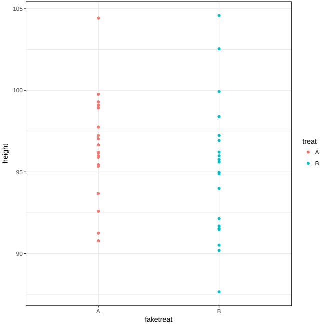

Cape Town weather

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Tessa Wessels, Faces on a Train

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