# Gov 99r: Lecture 6

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# Outline

# Experiments

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$$E[Y_0|D=1] - E[Y_0|D=0]$$

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The goal is to get at causality by identifying a set of observable outcomes (for the treated) that can stand in for the unobserved potential outcomes (for treated units as if they did not receive treatment)

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Here regression can be helpful to estimate "causal" effects.

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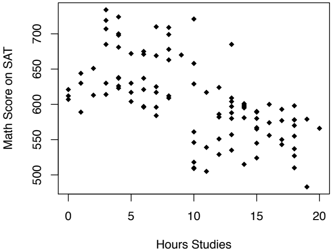

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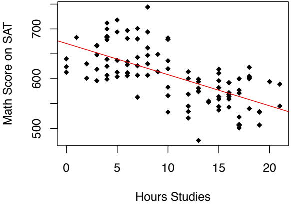

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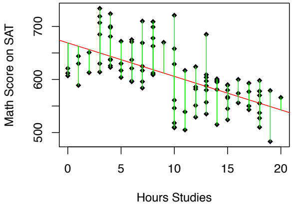

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Satisfying these assumptions fully will get you close to causal language, but for the most part you will be identifying correlation not causation

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