

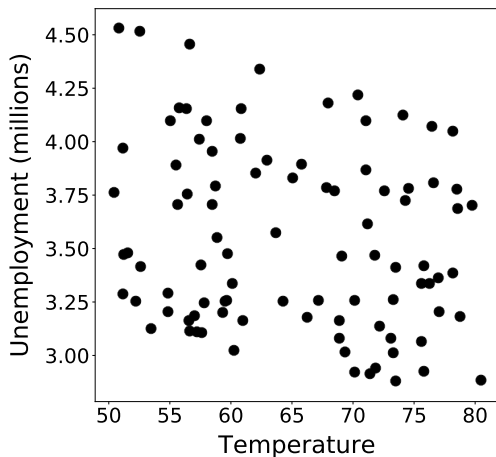
# Correlation (Usually) Does Not Imply Causation

## Probability and Statistics for Data Science

Carlos Fernandez-Granda



## Unemployment and temperature in Spain (2015-2022)



Correlation coefficient: -0.21

Would an increase in temperature decrease unemployment?

# Causal inference

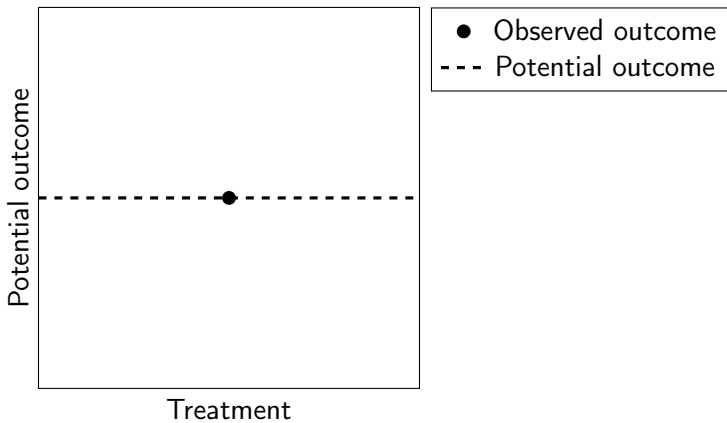
Key question: Does a treatment  $\tilde{t}$  cause a certain outcome?

Potential outcome:  $\widetilde{\text{po}}_t$

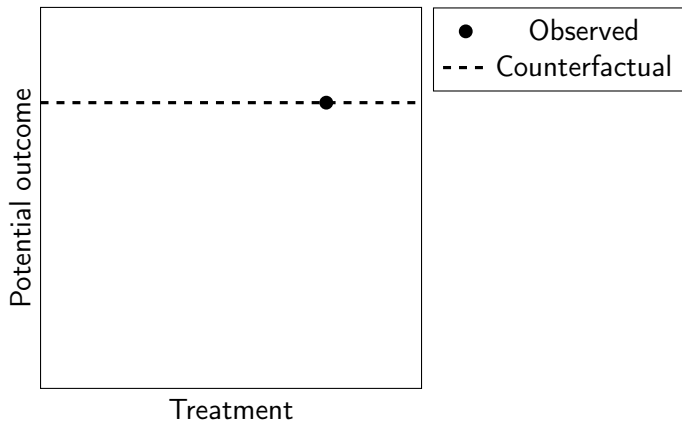
Observed data:

$$\tilde{y} := \widetilde{\text{po}}_t \quad \text{if} \quad \tilde{t} = t$$

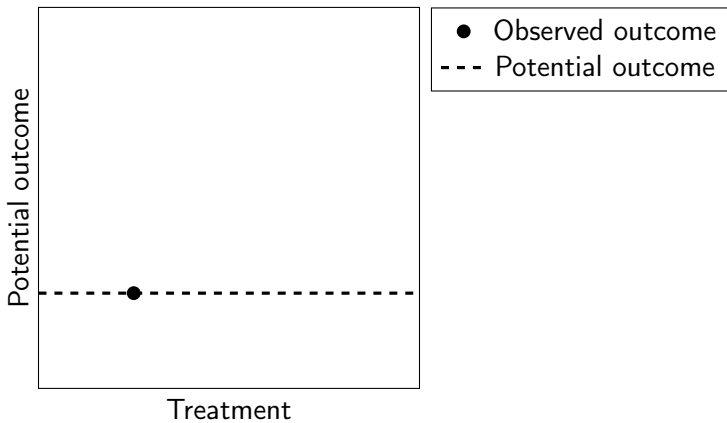
## Potential outcomes



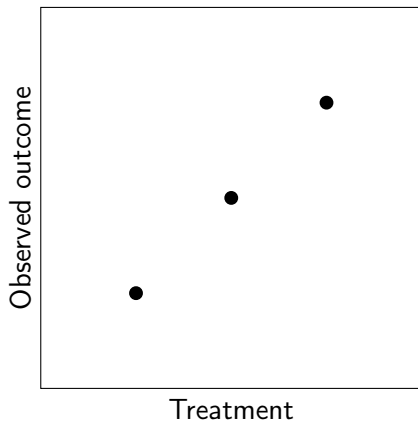
## Potential outcomes



## Potential outcomes



## Observed data



# Linear causal effect

For some constant  $\beta \in \mathbb{R}$

$$\mathbb{E} [\widetilde{\text{po}}_t] = \beta t$$

Key question: Can we estimate linear causal effects **from data**?



# Idea

Use covariance between observed outcome  $\tilde{y}$  and the treatment  $\tilde{t}$

Necessary condition:  $\widetilde{po}_t$  and  $\tilde{t}$  are **independent** for all  $t$

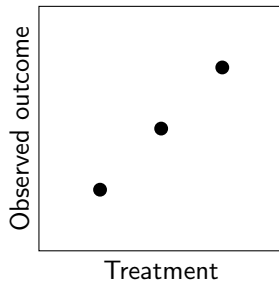
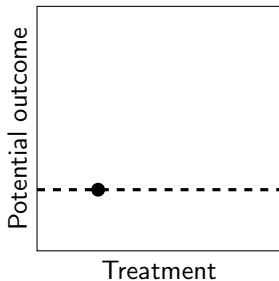
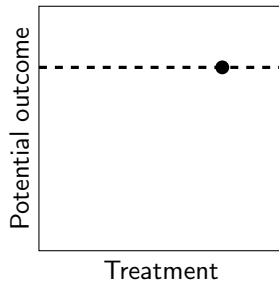
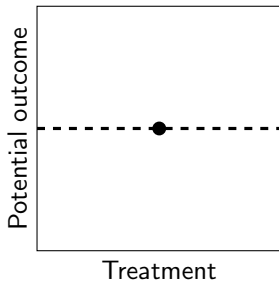
## Iterated expectation

Assuming  $E[\tilde{t}] = 0$  and  $E[\tilde{t}^2] = 1$

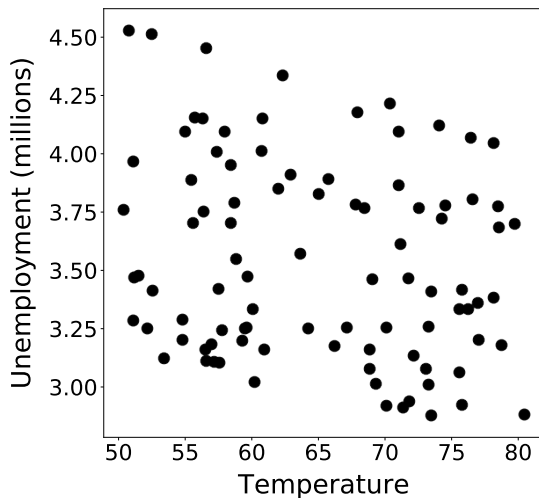
$$\begin{aligned}\text{Cov}[\tilde{y}, \tilde{t}] &= E[\tilde{y}\tilde{t}] = E\left[\mu_{\tilde{y}|\tilde{t}}(\tilde{t})\right] \\ &= E[\beta\tilde{t}^2] \\ &= \beta E[\tilde{t}^2] = \beta\end{aligned}$$

$$\begin{aligned}\mu_{\tilde{y}|\tilde{t}}(t) &= \int_{y=-\infty}^{\infty} yt f_{\tilde{y}|\tilde{t}}(y|t) dy \\ &= \int_{y=-\infty}^{\infty} yt f_{\widetilde{\text{po}}_t|\tilde{t}}(y|t) dy \\ &= t \int_{y=-\infty}^{\infty} y f_{\widetilde{\text{po}}_t}(y) dy \\ &= tE[\widetilde{\text{po}}_t] \\ &= \beta t^2\end{aligned}$$

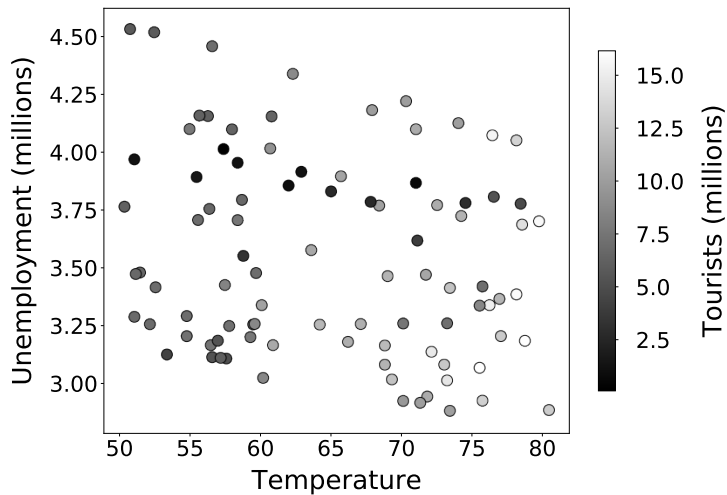
# Why do we need independence?



# Unemployment and temperature in Spain (2015-2022)



## Unemployment and temperature in Spain (2015-2022)



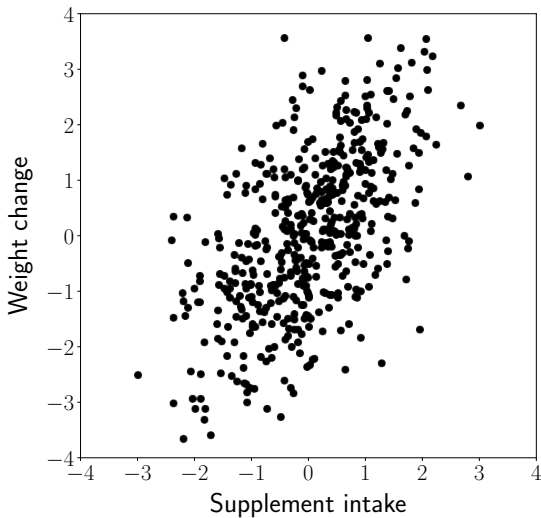
# Guinea-pig rescue

**Goal:** Fatten the guinea pigs

**Question:** Does a nutritional supplement help?

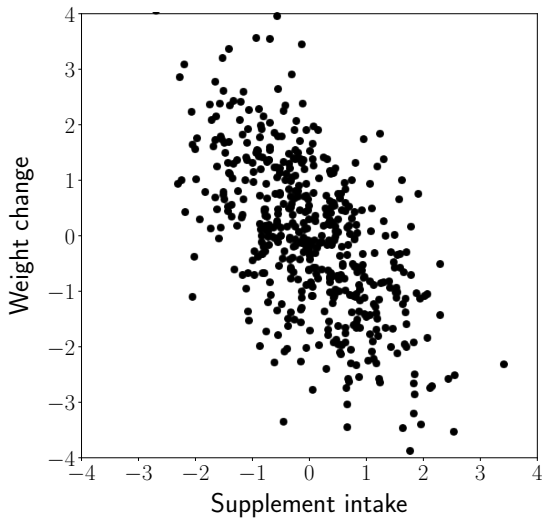
## Supplement mixed with food

Covariance = 0.8



## Supplement after the food

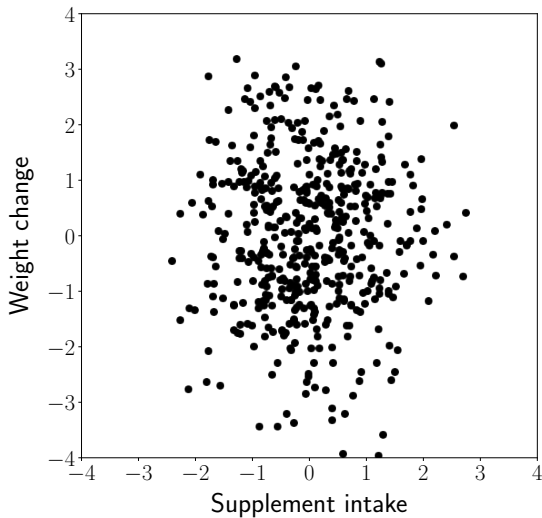
Covariance = -0.8





## Randomized supplement

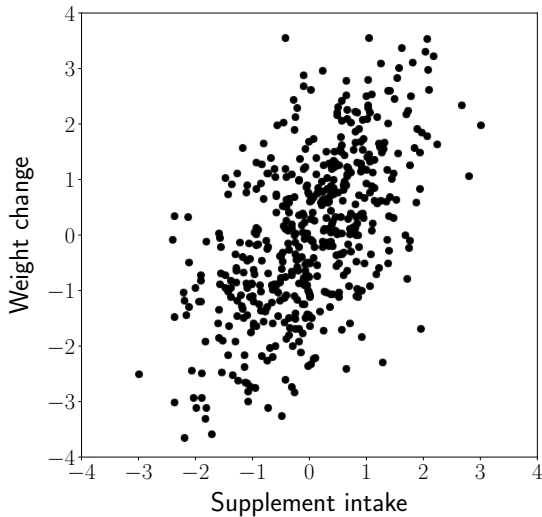
Covariance = 0



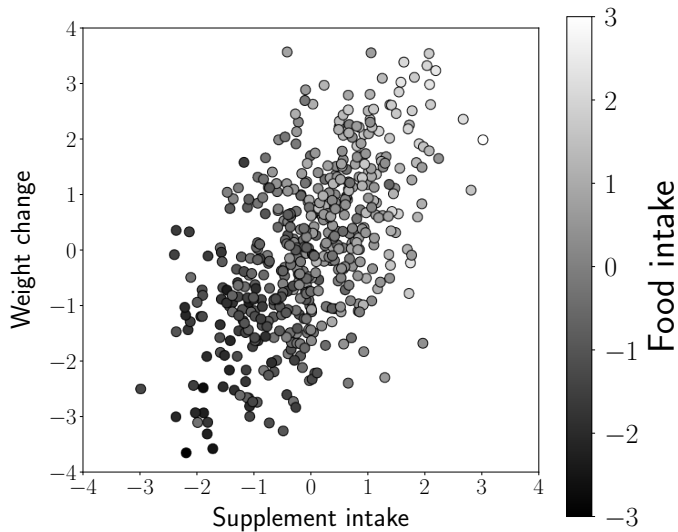
What's going on?

Weight change depends on food intake

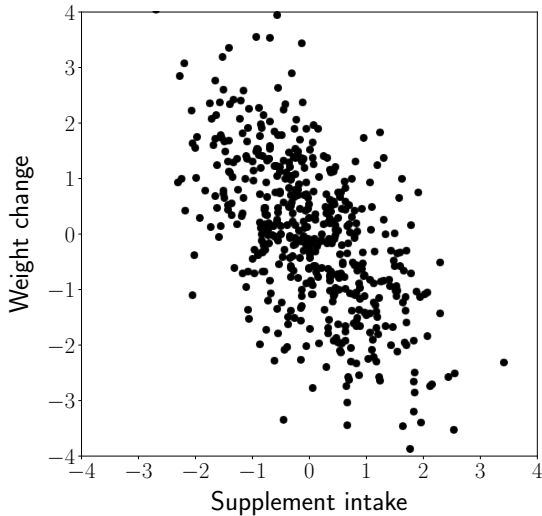
## Supplement mixed with food



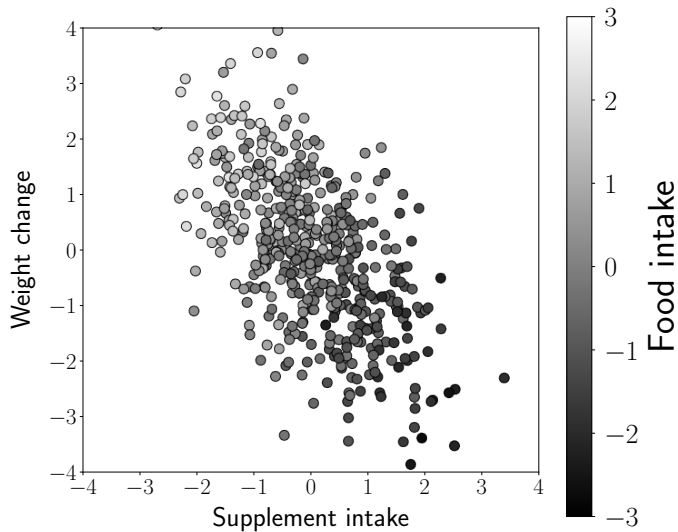
## Supplement mixed with food



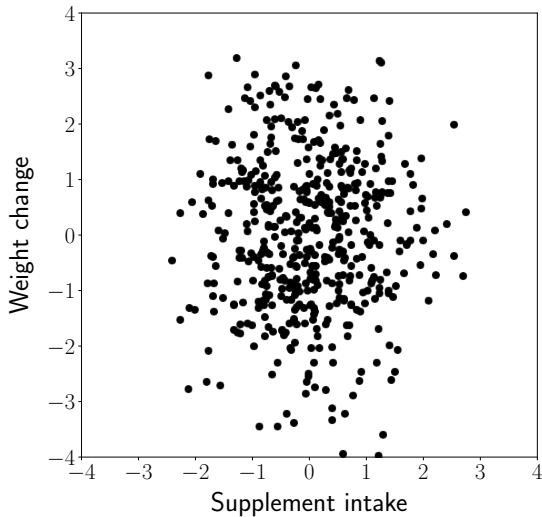
## Supplement after the food



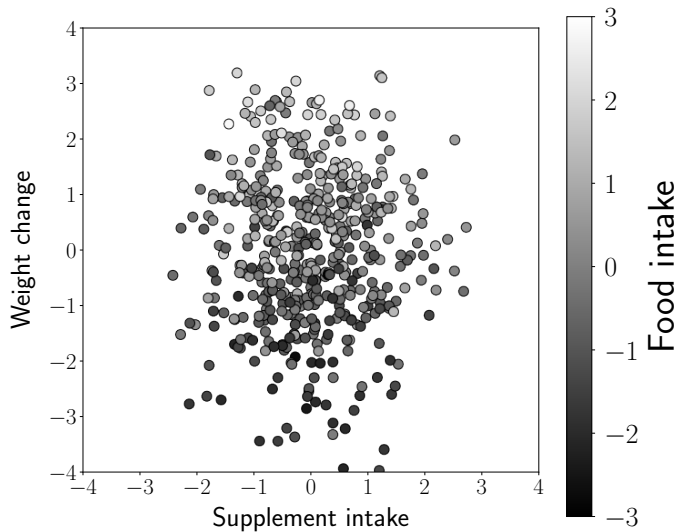
## Supplement after the food



## Randomized supplement



## Randomized supplement





# Unobserved confounder

Potential outcome  $\widetilde{\text{po}}_{t,c}$  depends on treatment  $\tilde{t}$  and on confounder  $\tilde{c}$

Observed data:

$$\tilde{y} := \widetilde{\text{po}}_{t,c} \quad \text{if} \quad \tilde{t} = t, \tilde{c} = c$$

For some constants  $\beta, \gamma \in \mathbb{R}$

$$\mathbb{E} [\widetilde{\text{po}}_{t,c}] = \beta t + \gamma c$$

Can we still estimate  $\beta$  from covariance between  $\tilde{t}$  and  $\tilde{y}$ ?

# Assumptions

$\tilde{t}$  and  $\tilde{c}$  are standardized

No additional confounders:  $\widetilde{\text{po}}_{t,c}$  is independent from  $(\tilde{t}, \tilde{c})$

## Iterated expectation

$$\begin{aligned}\text{Cov} [\tilde{y}, \tilde{t}] &= \text{E} [\tilde{y}\tilde{t}] = \text{E} \left[ \mu_{\tilde{y}\tilde{t} | \tilde{t}, \tilde{c}}(\tilde{t}, \tilde{c}) \right] \\ &= \text{E} [\beta \tilde{t}^2 + \gamma \tilde{t}\tilde{c}] \\ &= \beta \text{E} [\tilde{t}^2] + \gamma \text{E} [\tilde{t}\tilde{c}] \\ &= \beta + \gamma \rho_{\tilde{t}, \tilde{c}}\end{aligned}$$

$$\begin{aligned}\mu_{\tilde{y}\tilde{t} | \tilde{t}, \tilde{c}}(t, c) &= \int_{y=-\infty}^{\infty} yt f_{\tilde{y} | \tilde{t}, \tilde{c}}(y | t, c) dy \\ &= \int_{y=-\infty}^{\infty} yt f_{\widetilde{\text{po}}_{t,c} | \tilde{t}, \tilde{c}}(y | t, c) dy \\ &= t \int_{y=-\infty}^{\infty} y f_{\widetilde{\text{po}}_{t,c}}(y) dy \\ &= t \text{E} [\widetilde{\text{po}}_{t,c}] \\ &= \beta t^2 + \gamma ct\end{aligned}$$

# Guinea pigs

Treatment  $\tilde{t}$ : Supplement intake

Confounder  $\tilde{c}$ : Food intake

Potential outcome  $\widetilde{po}_{t,c}$ : Weight change

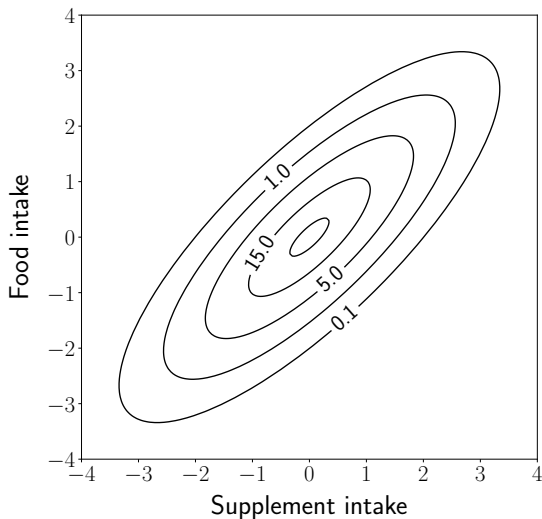
$$E[\widetilde{po}_{t,c}] = c$$

Covariance between observed weight change and supplement?

$$\text{Cov}[\tilde{y}, \tilde{t}] = \rho_{\tilde{t}, \tilde{c}}$$

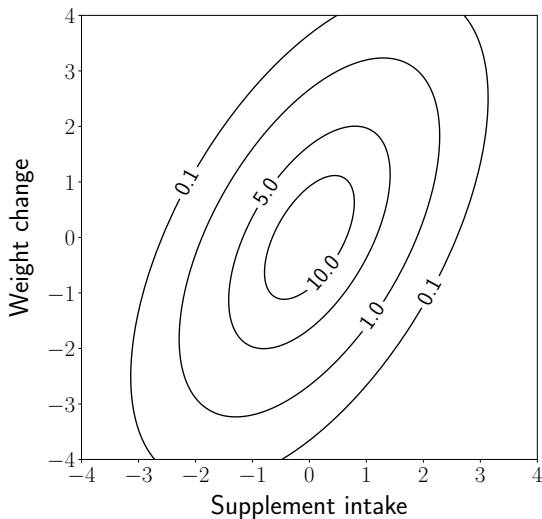
Supplement mixed with food:  $\rho_{\tilde{t}, \tilde{c}} := 0.8$

Assuming  $\tilde{t}$  and  $\tilde{c}$  are jointly Gaussian



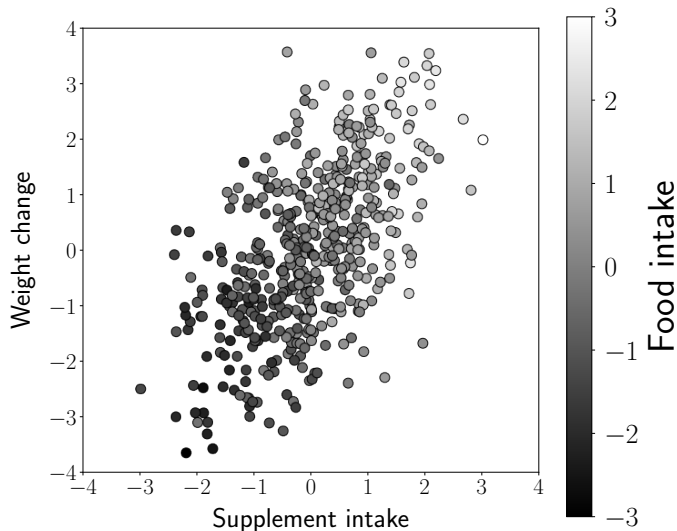
Supplement mixed with food:  $\text{Cov} [\tilde{y}, \tilde{t}] = 0.8$

Assuming  $\widetilde{\text{po}}_{t,c}$  is Gaussian with mean  $c$  and unit variance



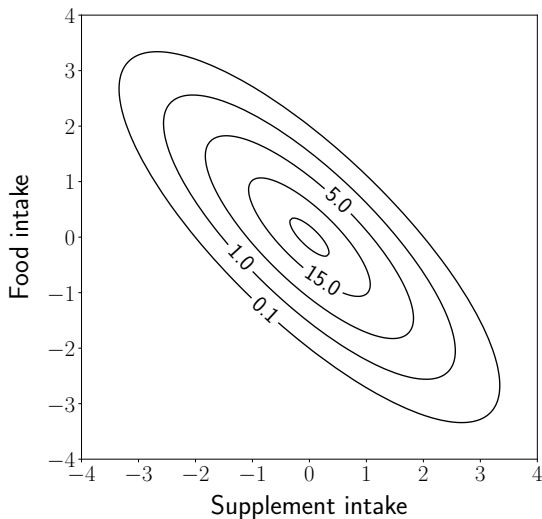
Supplement mixed with food:  $\text{Cov}[\tilde{y}, \tilde{t}] = 0.8$

Assuming  $\widetilde{\text{po}}_{t,c}$  is Gaussian with mean  $c$  and unit variance



Supplement after the food:  $\rho_{\tilde{t}, \tilde{c}} := -0.8$

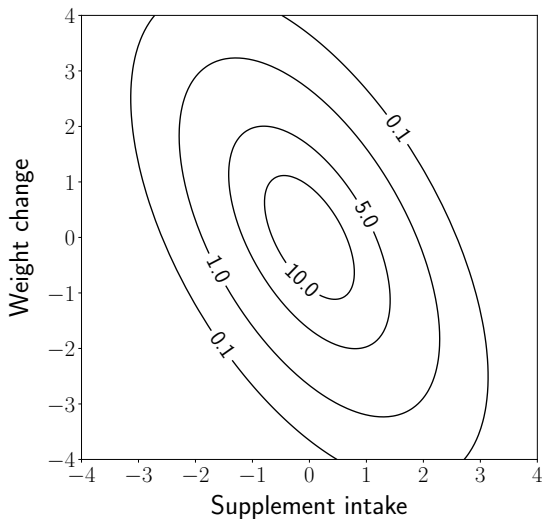
Assuming  $\tilde{t}$  and  $\tilde{c}$  are jointly Gaussian





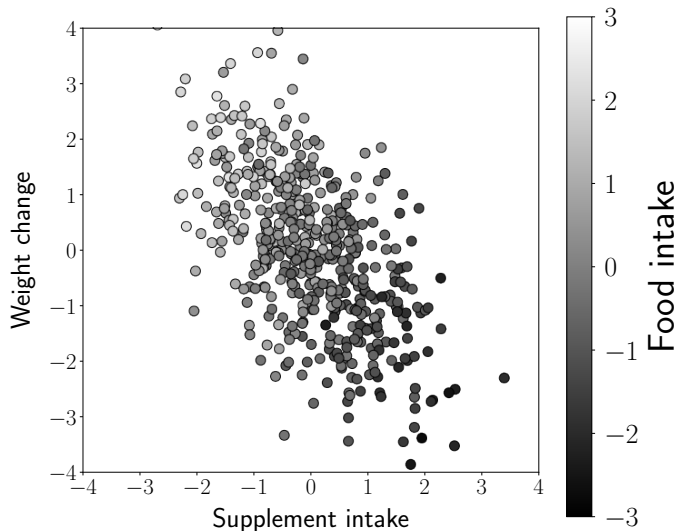
Supplement after the food:  $\text{Cov} [\tilde{y}, \tilde{t}] = -0.8$

Assuming  $\widetilde{\text{po}}_{t,c}$  is Gaussian with mean  $c$  and unit variance



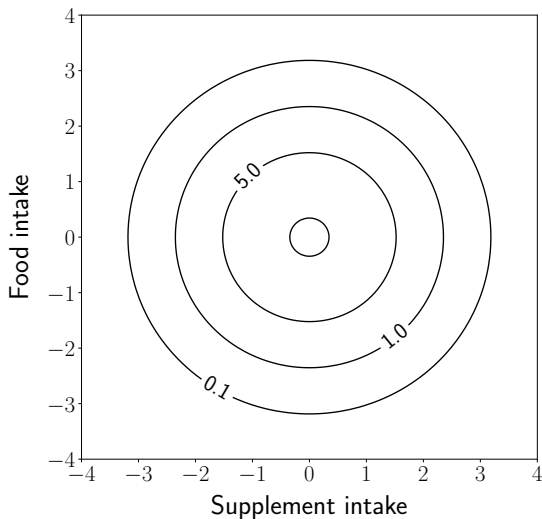
Supplement after the food:  $\text{Cov} [\tilde{y}, \tilde{t}] = -0.8$

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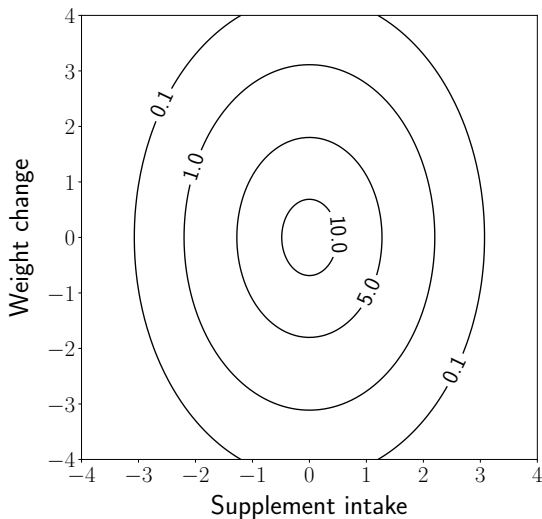
Randomized supplement:  $\rho_{\tilde{t}, \tilde{c}} := 0$

Assuming  $\tilde{t}$  and  $\tilde{c}$  are jointly Gaussian



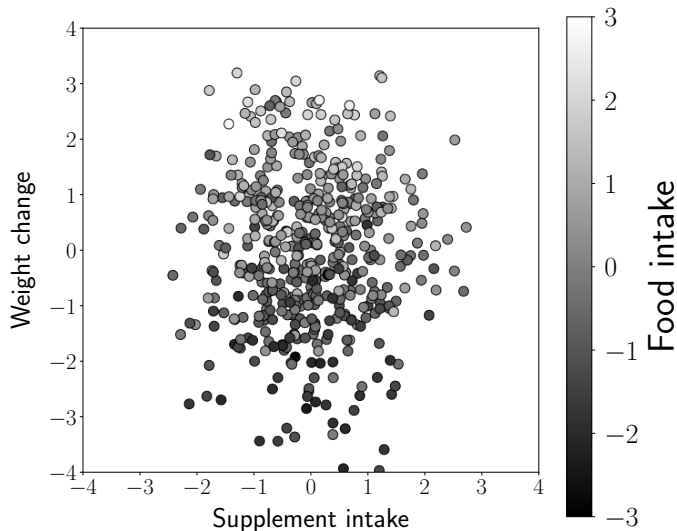
## Randomized supplement: $\text{Cov}[\tilde{y}, \tilde{t}] = 0$

Assuming  $\widetilde{\text{po}}_{t,c}$  is Gaussian with mean  $c$  and unit variance



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Assuming  $\widetilde{\text{po}}_{t,c}$  is Gaussian with mean  $c$  and unit variance



# What have we learned

Correlation does not imply causation

However, it does if the treatment is randomized

Otherwise, unobserved confounders produce spurious correlation