

Regression Stuff

EC 607, Set 05

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Prologue

Schedule

Last time: Inference and simulation

Let's review using a quote from *MHE*

We've chosen to start with the **asymptotic approach to inference** because modern empirical work typically leans heavily on the large-sample theory that lies behind robust variance formulas. The **payoff is valid inference under weak assumptions**, in particular, a framework that makes sense for our less-than-literal approach to regression models. On the other hand, the **large-sample approach is not without its dangers...**

MHE, p. 48 (emphasis added)

Schedule

Today

Regression and causality

Read MHE 3.2

Upcoming

Project, step 1

Assignment #2

Advice Make sure you're taking a few minutes for personal health.[†]

[†] *health* = physical, mental, and spiritual. Also: Do a better job than I do.

Regression talk

Saturated models

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$$\text{Wages}_i = \alpha + \beta_1 \mathbb{I}\{s_i = 1\}_i + \beta_2 \mathbb{I}\{s_i = 2\}_i + \dots + \beta_T \mathbb{I}\{s_i = T\}_i + \varepsilon_i$$

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Here, $s_i = 0$ is our reference level; β_j is the effect of j years of schooling.

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Here, $s_i = 0$ is our reference level; β_j is the effect of j years of schooling.

$$E[\text{Wages}_i \mid s_i = j] - E[\text{Wages}_i \mid s_i = 0] = \alpha + \beta_j - \alpha = \beta_j$$

Regression talk

Saturated models

Q Why focus on saturated models?

Regression talk

Saturated models

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A Saturated models perfectly fit the CEF

Regression talk

Saturated models

Q Why focus on saturated models?

A **Saturated models perfectly fit the CEF** because the CEF is a linear function of the dummy variables—a special case of the linear CEF theorem.

Regression talk

Saturated models

If you have multiple explanatory variables, you need **interactions**.

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Example₃ Regressing **Wages** on **College Graduation** and **Gender**.

$$\begin{aligned} \text{Wages}_i = & \alpha + \beta_1 \mathbb{I}\{\text{College Graduate}\}_i + \beta_2 \mathbb{I}\{\text{Female}\}_i \\ & + \beta_3 \mathbb{I}\{\text{College Graduate}\}_i \times \mathbb{I}\{\text{Female}\}_i + \varepsilon_i \end{aligned}$$

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Here, the uninteracted terms (β_1 & β_2) are called **main effects**; β_3 gives the effect of the **interaction**.

Regression talk

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Here, the uninteracted terms (β_1 & β_2) are called **main effects**; β_3 gives the effect of the **interaction**.

$$E[\text{Wages}_i | \text{College Graduate}_i = 0, \text{Female}_i = 0] = \alpha$$

$$E[\text{Wages}_i | \text{College Graduate}_i = 1, \text{Female}_i = 0] = \alpha + \beta_1$$

$$E[\text{Wages}_i | \text{College Graduate}_i = 0, \text{Female}_i = 1] = \alpha + \beta_2$$

$$E[\text{Wages}_i | \text{College Graduate}_i = 1, \text{Female}_i = 1] = \alpha + \beta_1 + \beta_2 + \beta_3$$

Regression talk

Saturated models

The CEF can take on four possible values,

$$E[\text{Wages}_i | \text{College Graduate}_i = 0, \text{Female}_i = 0] = \alpha$$

$$E[\text{Wages}_i | \text{College Graduate}_i = 1, \text{Female}_i = 0] = \alpha + \beta_1$$

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$$E[\text{Wages}_i | \text{College Graduate}_i = 1, \text{Female}_i = 1] = \alpha + \beta_1 + \beta_2 + \beta_3$$

and the specification of our saturated regression model

$$\begin{aligned} \text{Wages}_i = & \alpha + \beta_1 \mathbb{I}\{\text{College Graduate}\}_i + \beta_2 \mathbb{I}\{\text{Female}\}_i \\ & + \beta_3 \mathbb{I}\{\text{College Graduate}\}_i \times \mathbb{I}\{\text{Female}\}_i + \varepsilon_i \end{aligned}$$

does not restrict the CEF at all.

Regression talk

Model specification

Saturated models sit at one extreme of the model-specification spectrum, with *linear, uninteracted models* occupying the opposite extreme.

Saturated models

- Fit CEF (+)
- Complex (–)
 - Many dummies
 - Many interactions

Plain, linear models

- Linear approximations (–)
- Simple (+)

Regression talk

Model specification

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- Linear approximations (–)
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Don't forget there are many options in between—though some make less sense than others (*e.g.*, interactions without main effects).

Regression talk

Model specification

Note Saturated models perfectly fit the CEF regardless of Y_i 's distribution.

Regression talk

Model specification

Note Saturated models perfectly fit the CEF regardless of Y_i 's distribution.

Continuous, linear probability, logged, non-negative—it works for all.

Now back to causality...

Regression and causality

Regression and causality

The return of causality

We've spent the last few lectures developing properties/understanding of (1) the CEF and (2) least-squares regression.

Let's return to our main goal of the course...

Q When can we actually interpret a regression as **causal**?[†]

[†] *Hint:* There is no "reg y x, causal" command in Stata.

Regression and causality

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A A regression is causal when the CEF it approximates is causal.

[†] *Hint:* There is no "reg y x, causal" command in Stata.

Regression and causality

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Great... thanks.

Q So when is a CEF causal?

Regression and causality

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Great... thanks.

Q So when is a CEF causal?

A First, return to the potential-outcomes framework, describing hypothetical outcomes.

A CEF is causal when it describes **differences in average potential outcomes** for a fixed reference population.

MHE, p. 52 (emphasis added)

Regression and causality

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Great... thanks.

Q So when is a CEF causal?

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MHE, p. 52 (emphasis added)

Let's work through this "definition" of causal CEFs with an example.

Regression and causality

Causal CEFs

Example The (causal) effect of schooling on income.

Regression and causality

Causal CEFs

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The causal effect of schooling for individual i would tell us how i 's **earnings** Y_i would change if we varied i 's **level of schooling** s_i .

Regression and causality

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Previously, we discussed how experiments randomly assign treatment to *ensure the variable of interest is independent of potential outcomes*.

Regression and causality

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Now we would like to **extend this framework** to

1. variables that take on **more than two values**
2. situations that require us to **hold many covariates constant** in order to achieve a valid causal interpretation

Regression and causality

Causal CEFs

The idea of *holding (many) covariates constant* brings us to one of the cornerstones of applied econometrics: the **conditional independence assumption (CIA)** (also called *selection on observables*).

Regression and causality

The conditional independence assumption

Definition(s)

- Conditional on some set of covariates \mathbf{X}_i , selection bias disappears.

Regression and causality

The conditional independence assumption

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$$\{Y_{0i}, Y_{1i}\} \perp\!\!\!\perp D_i | \mathbf{X}_i$$

Regression and causality

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To see how CIA eliminates selection bias...

$$\text{Selection bias} = E[Y_{0i} | \mathbf{X}_i, D_i = 1] - E[Y_{0i} | \mathbf{X}_i, D_i = 0]$$

Regression and causality

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Regression and causality

The conditional independence assumption

Another way you'll hear CIA: After controlling for some set of variables \mathbf{X}_i , treatment assignment is ***as good as random***.

Regression and causality

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To see how this assumption[†] buys us a causal interpretation, write out our old difference in means—but now condition on \mathbf{X}_i .

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Regression and causality

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$$\begin{aligned} & E[\mathbf{Y}_i \mid \mathbf{X}_i, \mathbf{D}_i = 1] - E[\mathbf{Y}_i \mid \mathbf{X}_i, \mathbf{D}_i = 0] \\ &= E[\mathbf{Y}_{1i} \mid \mathbf{X}_i] - E[\mathbf{Y}_{0i} \mid \mathbf{X}_i] \\ &= E[\mathbf{Y}_{1i} - \mathbf{Y}_{0i} \mid \mathbf{X}_i] \end{aligned}$$

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$$\begin{aligned} & E[Y_i \mid \mathbf{X}_i, D_i = 1] - E[Y_i \mid \mathbf{X}_i, D_i = 0] \\ &= E[Y_{1i} \mid \mathbf{X}_i] - E[Y_{0i} \mid \mathbf{X}_i] \\ &= E[Y_{1i} - Y_{0i} \mid \mathbf{X}_i] \end{aligned}$$

Even randomized experiments need the CIA—e.g., the STAR experiment's *within-school* randomization.

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The conditional independence assumption

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Regression and causality

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We want to know the effect of an individual's **schooling** on her **wages** (Y_i).

Regression and causality

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Now, Y_{si} denotes individual i 's outcome **with s years of schooling**.

Regression and causality

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Let each individual have her own function between **schooling** and **earnings**.

$$Y_{si} \equiv f_i(s)$$

$f_i(s)$ answers exactly the type of causal questions that we want to answer.

Regression and causality

The conditional independence assumption

Extending the CIA to this multi-valued setting...

$$Y_{s_i} \perp\!\!\!\perp s_i \mid \mathbf{X}_i \text{ for all } s$$

Regression and causality

The conditional independence assumption

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If we apply the CIA to $Y_{si} \equiv f_i(s)$, we define the *average causal effect* of a one-year increase in *schooling* as

$$E[f_i(s) - f_i(s - 1) \mid \mathbf{X}_i]$$

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However, the data only contain one realization of $f_i(s)$ per i —we only see $f_i(s)$ evaluated at exactly one value of s per i , i.e., $Y_i = f_i(s_i)$.

Regression and causality

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Regression and causality

The conditional independence assumption

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The CIA to the rescue! Conditional on X_i , Y_{si} and s_i are independent.

Regression and causality

The conditional independence assumption

The CIA to the rescue! Conditional on \mathbf{X}_i , Y_{si} and s_i are independent.

$$\begin{aligned} & E[Y_i \mid \mathbf{X}_i, s_i = s] - E[Y_i \mid \mathbf{X}_i, s_i = s - 1] \\ &= E[Y_{si} \mid \mathbf{X}_i, s_i = s] - E[Y_{(s-1)i} \mid \mathbf{X}_i, s_i = s - 1] \\ &= E[Y_{si} \mid \mathbf{X}_i] - E[Y_{(s-1)i} \mid \mathbf{X}_i] \\ &= E[Y_{si} - Y_{(s-1)i} \mid \mathbf{X}_i] \\ &= E[f_i(s) - f_i(s - 1) \mid \mathbf{X}_i] \end{aligned}$$

Regression and causality

The conditional independence assumption

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With the CIA, a difference in conditional averages allows causal interpretations.

Regression and causality

The conditional independence assumption

Example The causal effect of high-school graduation is

Regression and causality

The conditional independence assumption

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$$E[Y_i | X_i, s_i = 12] - E[Y_i | X_i, s_i = 11]$$

Regression and causality

The conditional independence assumption

Example The causal effect of high-school graduation is

$$\begin{aligned} & E[Y_i | X_i, s_i = 12] - E[Y_i | X_i, s_i = 11] \\ &= E[f_i(12) | X_i, s_i = 12] - E[f_i(11) | X_i, s_i = 11] \end{aligned}$$

Regression and causality

The conditional independence assumption

Example The causal effect of high-school graduation is

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Regression and causality

The conditional independence assumption

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Regression and causality

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Regression and causality

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Regression and causality

The conditional independence assumption

Q What about the **unconditional** average causal effect of graduation?

Regression and causality

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A First, remember what we just showed...

Regression and causality

The conditional independence assumption

Q What about the **unconditional** average causal effect of graduation?

A First, remember what we just showed...

$$E[Y_i | \mathbf{X}_i, s_i = 12] - E[Y_i | \mathbf{X}_i, s_i = 11] = E[f_i(12) - f_i(11) | \mathbf{X}_i]$$

Regression and causality

The conditional independence assumption

Q What about the **unconditional** average causal effect of graduation?

A First, remember what we just showed...

$$E[Y_i | \mathbf{X}_i, s_i = 12] - E[Y_i | \mathbf{X}_i, s_i = 11] = E[f_i(12) - f_i(11) | \mathbf{X}_i]$$

Now take the expected value of both sides and apply the LIE.

$$\begin{aligned} & E\left(E[Y_i | \mathbf{X}_i, s_i = 12] - E[Y_i | \mathbf{X}_i, s_i = 11] \right) \\ &= E\left(E[f_i(12) - f_i(11) | \mathbf{X}_i] \right) \end{aligned}$$

Regression and causality

The conditional independence assumption

Q What about the **unconditional** average causal effect of graduation?

A First, remember what we just showed...

$$E[Y_i | \mathbf{X}_i, s_i = 12] - E[Y_i | \mathbf{X}_i, s_i = 11] = E[f_i(12) - f_i(11) | \mathbf{X}_i]$$

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Regression and causality

The conditional independence assumption

Takeaways

1. Conditional independence gives our parameters **causal interpretations** (eliminating selection bias).

Regression and causality

The conditional independence assumption

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Regression and causality

The conditional independence assumption

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1. Conditional independence gives our parameters **causal interpretations** (eliminating selection bias).
2. The interpretation changes slightly—without iterating expectations, we have **conditional average treatment effects**.
3. The CIA is challenging—you need to know which set of covariates (\mathbf{X}_i) leads to **as-good-as-random residual variation in your treatment**.

Regression and causality

The conditional independence assumption

Takeaways

1. Conditional independence gives our parameters **causal interpretations** (eliminating selection bias).
2. The interpretation changes slightly—without iterating expectations, we have **conditional average treatment effects**.
3. The CIA is challenging—you need to know which set of covariates (\mathbf{X}_i) leads to **as-good-as-random residual variation in your treatment**.
4. The idea of conditioning on observables to match *comparable* individuals introduces us to **matching estimators**—comparing groups of individuals with the same covariate values.

Regression and causality

From the CIA to regression

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Regression and causality

From the CIA to regression

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Regression and causality

From the CIA to regression

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2. If we allow $f_i(\mathbf{s})$ to be nonlinear in \mathbf{s} and heterogeneous across i , regression provides a weighted average of individual-specific differences $f_i(\mathbf{s}) - f_i(\mathbf{s} - \mathbf{1})$.[†]

[†] Leads to a matching-style estimator.

Regression and causality

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Let's start with the 'easier' case: a linear, constant-effects (causal) model.

[†] Leads to a matching-style estimator.

Regression and causality

From the CIA to regression

Let $f_i(\mathbf{s})$ be linear in \mathbf{s} and equal across i except for an error term, e.g.,

$$f_i(\mathbf{s}) = \alpha + \rho\mathbf{s} + \eta_i \quad (\text{A})$$

Regression and causality

From the CIA to regression

Let $f_i(s)$ be linear in s and equal across i except for an error term, e.g.,

$$f_i(s) = \alpha + \rho s + \eta_i \quad (\text{A})$$

Substitute in our observed value of s_i and the outcome Y_i

$$Y_i = \alpha + \rho s_i + \eta_i \quad (\text{B})$$

Regression and causality

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Let $f_i(\mathbf{s})$ be linear in \mathbf{s} and equal across i except for an error term, e.g.,

$$f_i(\mathbf{s}) = \alpha + \rho\mathbf{s} + \eta_i \quad (\text{A})$$

Substitute in our observed value of \mathbf{s}_i and the outcome Y_i

$$Y_i = \alpha + \rho\mathbf{s}_i + \eta_i \quad (\text{B})$$

While ρ in (A) is explicitly causal, regression-based estimates of ρ in (B) need not be causal (selection/OVB for endogenous \mathbf{s}_i).

Regression and causality

From the CIA to regression

Continuing with our linear, constant-effect causal model...

$$f_i(\mathbf{s}) = \alpha + \rho\mathbf{s} + \eta_i \quad (\text{A})$$

Now impose the conditional independence assumption for covariates \mathbf{X}_i .

$$\eta_i = \mathbf{X}_i' \boldsymbol{\gamma} + \nu_i \quad (\text{C})$$

where $\boldsymbol{\gamma}$ is a vector of population coefficients from regressing η_i on \mathbf{X}_i .

Regression and causality

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where $\boldsymbol{\gamma}$ is a vector of population coefficients from regressing η_i on \mathbf{X}_i .

Note Least-squares regression implies

1. $E[\eta_i | \mathbf{X}_i] = \mathbf{X}_i' \boldsymbol{\gamma}$
2. \mathbf{X}_i is uncorrelated with ν_i .

Regression and causality

From the CIA to regression

Now write out the conditional expectation function of $f_i(\mathbf{s})$ on \mathbf{X}_i and \mathbf{s}_i .

$$\begin{aligned} & E[f_i(\mathbf{s}) \mid \mathbf{X}_i, \mathbf{s}_i] \\ &= E[f_i(\mathbf{s}) \mid \mathbf{X}_i] \quad (\text{CIA}) \end{aligned}$$

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Regression and causality

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Now write out the conditional expectation function of $f_i(\mathbf{s})$ on \mathbf{X}_i and \mathbf{s}_i .

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The CEF of $f_i(\mathbf{s}_i)$ is linear, which means that the (right[†]) population regression will be the CEF.

[†] Here, "right" means conditional on \mathbf{X}_i .

Regression and causality

From the CIA to regression

Thus, the linear causal (regression) model is

$$Y_i = \alpha + \rho s_i + \mathbf{X}_i' \gamma + \nu_i$$

The residual ν_i is uncorrelated with

1. s_i (from the CIA)
2. \mathbf{X}_i (from defining γ via the regression of η on \mathbf{X}_i)

The coefficient ρ gives the causal effect of s_i on Y_i .

Regression and causality

From the CIA to regression

As Angrist and Pischke note, this **conditional-independence assumption** (*a.k.a.* the selection-on-observables assumption) is the cornerstone of modern empirical work in economics—and many other disciplines.

Nearly any empirical application that wants a causal interpretation involves a (sometimes implicit) argument that **conditional on some set of covariates, treatment is as-good-as random.**

Regression and causality

From the CIA to regression

As Angrist and Pischke note, this **conditional-independence assumption** (*a.k.a.* the selection-on-observables assumption) is the cornerstone of modern empirical work in economics—and many other disciplines.

Nearly any empirical application that wants a causal interpretation involves a (sometimes implicit) argument that **conditional on some set of covariates, treatment is as-good-as random.**

Part of our job: Reasoning through the validity of this assumption.

Regression and causality

CIA example

Let's continue with the returns to graduation (G_i).

Let's imagine

1. Women are more likely to graduate.
2. Everyone receives the same return to graduation.
3. Women receive lower wages across the board.

Regression and causality

CIA example

First, we need to generate some data.

```
# Set seed
set.seed(12345)
# Set sample size
n = 1e4
# Generate data
ex_df = tibble(
  female = rep(c(0, 1), each = n/2),
  grad = runif(n, min = female/3, max = 1) %>% round(0),
  wage = 100 - 25 * female + 5 * grad + rnorm(n, sd = 3)
)
```


Regression and causality

CIA example

Now we can estimate our naïve regression

$$\text{Wage}_i = \alpha + \beta \text{Grad}_i + \varepsilon_i$$

Regression and causality

CIA example

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```
lm(wage ~ grad, data = ex_df)
```

	Coef.	S.E.	t stat
Intercept	91.65	0.20	447.70
Graduate	-1.59	0.26	-6.18

Regression and causality

CIA example

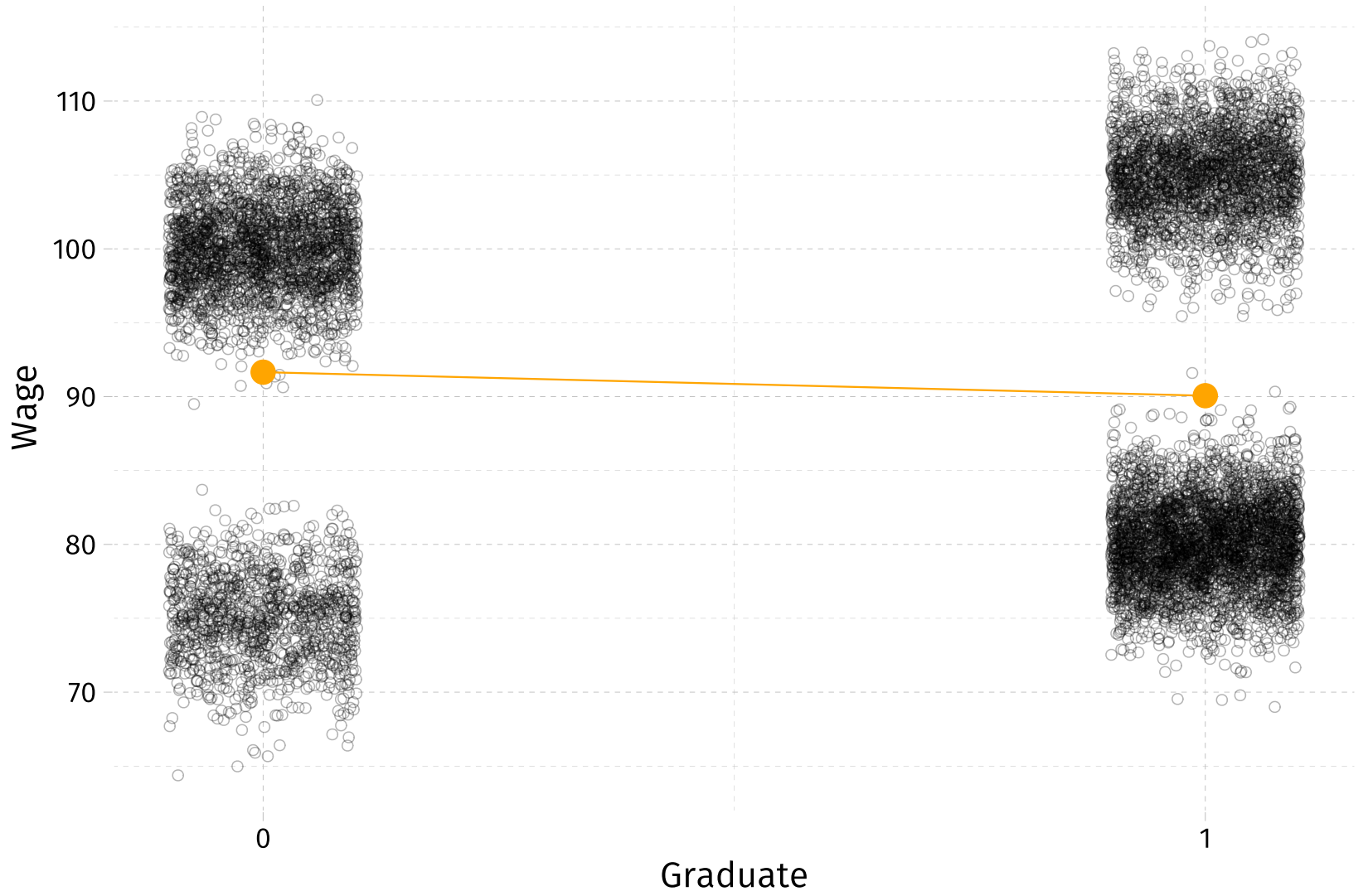
Now we can estimate our naïve regression

$$\text{Wage}_i = \alpha + \beta \text{Grad}_i + \varepsilon_i$$

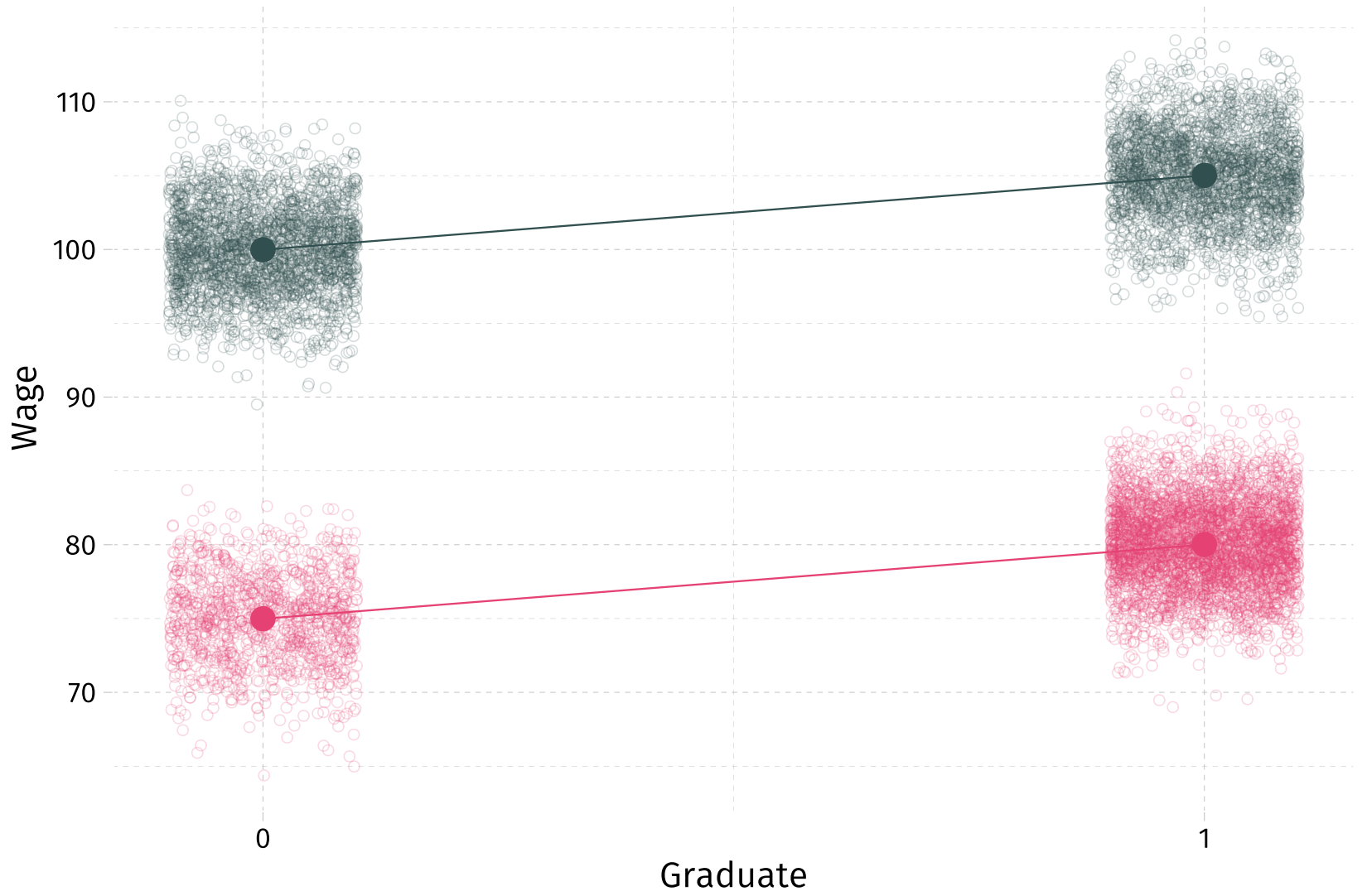
```
lm(wage ~ grad, data = ex_df)
```

	Coef.	S.E.	t stat
Intercept	91.65	0.20	447.70
Graduate	-1.59	0.26	-6.18

Maybe we should have plotted our data...



We're still missing something...



Regression and causality

CIA example

Now we can estimate our causal regression

$$\text{Wage}_i = \alpha + \beta_1 \text{Grad}_i + \beta_2 \text{Female}_i + \varepsilon_i$$

Regression and causality

CIA example

Now we can estimate our causal regression

$$\text{Wage}_i = \alpha + \beta_1 \text{Grad}_i + \beta_2 \text{Female}_i + \varepsilon_i$$

```
lm(wage ~ grad + female, data = ex_df)
```

	Coef.	S.E.	t stat
Intercept	99.98	0.05	1868.81
Graduate	5.03	0.06	78.23
Female	-25.00	0.06	-402.64

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