

# Lecture 09

OLS // Regression

---

Ivan Rudik  
AEM 4510

# Roadmap

- Intro to regression and ordinary least squares

# Regression and ordinary least squares

---

# Why?

Let's start with a few **basic, general questions**

# Why?

Let's start with a few **basic, general questions**

1. What is the goal of econometrics?
2. Why do economists (or other people) study or use econometrics?

# Why?

Let's start with a few **basic, general questions**

1. What is the goal of econometrics?
2. Why do economists (or other people) study or use econometrics?

**One simple answer:** Learn about the world using data

# Why? Example

GPA is an output from endowments (ability), and hours studied (inputs), and pollution exposure (externality)

# Why? Example

GPA is an output from endowments (ability), and hours studied (inputs), and pollution exposure (externality)

One might hypothesize a model:  $\text{GPA} = f(I, P, \text{SAT}, H)$

where  $H$  is hours studied,  $P$  is pollution exposure, SAT is SAT score and I is family income

# Why? Example

GPA is an output from endowments (ability), and hours studied (inputs), and pollution exposure (externality)

One might hypothesize a model:  $\text{GPA} = f(I, P, \text{SAT}, H)$

where  $H$  is hours studied,  $P$  is pollution exposure, SAT is SAT score and I is family income

We expect that GPA will rise with some variables, and decrease with others

# Why? Example

GPA is an output from endowments (ability), and hours studied (inputs), and pollution exposure (externality)

One might hypothesize a model:  $\text{GPA} = f(I, P, \text{SAT}, H)$

where  $H$  is hours studied,  $P$  is pollution exposure, SAT is SAT score and I is family income

We expect that GPA will rise with some variables, and decrease with others

But who needs to *expect*?

# Why? Example

GPA is an output from endowments (ability), and hours studied (inputs), and pollution exposure (externality)

One might hypothesize a model:  $\text{GPA} = f(I, P, \text{SAT}, H)$

where  $H$  is hours studied,  $P$  is pollution exposure, SAT is SAT score and I is family income

We expect that GPA will rise with some variables, and decrease with others

But who needs to *expect*?

We can test these hypotheses **using a regression model**

# How?

We can write down a linear regression model of the relationship between GPA and (H, P, SAT, PCT):

$$\text{GPA}_i = \beta_0 + \beta_1 I_i + \beta_2 P_i + \beta_3 \text{SAT}_i + \beta_4 H_i + \varepsilon_i$$

# How?

We can write down a linear regression model of the relationship between GPA and (H, P, SAT, PCT):

$$\text{GPA}_i = \beta_0 + \beta_1 I_i + \beta_2 P_i + \beta_3 \text{SAT}_i + \beta_4 H_i + \varepsilon_i$$

The left hand side of the equals sign is our **dependent variable** GPA

# How?

We can write down a linear regression model of the relationship between GPA and (H, P, SAT, PCT):

$$\text{GPA}_i = \beta_0 + \beta_1 I_i + \beta_2 P_i + \beta_3 \text{SAT}_i + \beta_4 H_i + \varepsilon_i$$

The left hand side of the equals sign is our **dependent variable** GPA

The right hand side of the equals sign contains all of our **independent variables** (I, P, SAT, H), and an error term  $\varepsilon_i$  (described later)

# How?

We can write down a linear regression model of the relationship between GPA and (H, P, SAT, PCT):

$$\text{GPA}_i = \beta_0 + \beta_1 I_i + \beta_2 P_i + \beta_3 \text{SAT}_i + \beta_4 H_i + \varepsilon_i$$

The left hand side of the equals sign is our **dependent variable** GPA

The right hand side of the equals sign contains all of our **independent variables** (I, P, SAT, H), and an error term  $\varepsilon_i$  (described later)

The subscript  $i$  means that the variable contains the value for some person  $i$  in our dataset where  $i = 1, \dots, N$

# How?

$$\text{GPA}_i = \beta_0 + \beta_1 I_i + \beta_2 P_i + \beta_3 \text{SAT}_i + \beta_4 H_i + \varepsilon_i$$

We are interested in how pollution  $P$  affects GPA

# How?

$$\text{GPA}_i = \beta_0 + \beta_1 I_i + \beta_2 P_i + \beta_3 \text{SAT}_i + \beta_4 H_i + \varepsilon_i$$

We are interested in how pollution  $P$  affects GPA

This is given by  $\beta_2$

# How?

$$\text{GPA}_i = \beta_0 + \beta_1 I_i + \beta_2 P_i + \beta_3 \text{SAT}_i + \beta_4 H_i + \varepsilon_i$$

We are interested in how pollution  $P$  affects GPA

This is given by  $\beta_2$

Notice that  $\beta_2 = \frac{\partial \text{GPA}_i}{\partial P_i}$

# How?

$$\text{GPA}_i = \beta_0 + \beta_1 I_i + \beta_2 P_i + \beta_3 \text{SAT}_i + \beta_4 H_i + \varepsilon_i$$

We are interested in how pollution  $P$  affects GPA

This is given by  $\beta_2$

Notice that  $\beta_2 = \frac{\partial \text{GPA}_i}{\partial P_i}$

$\beta_2$  tells us how GPA changes, given a 1 unit increase in pollution!

# How?

$$\text{GPA}_i = \beta_0 + \beta_1 I_i + \beta_2 P_i + \beta_3 \text{SAT}_i + \beta_4 H_i + \varepsilon_i$$

We are interested in how pollution P affects GPA

This is given by  $\beta_2$

Notice that  $\beta_2 = \frac{\partial \text{GPA}_i}{\partial P_i}$

$\beta_2$  tells us how GPA changes, given a 1 unit increase in pollution!

Our goal will be to estimate  $\beta_2$ , we denote estimates with hats:  $\hat{\beta}_2$

# How?

How do we estimate  $\beta_2$ ?

# How?

How do we estimate  $\beta_2$ ?

First, suppose we have a set of estimates for all of our  $\beta$ s, then we can *estimate* the GPA ( $\widehat{GPA}_i$ ) for any given person based on just (I, P, SAT, H):

$$\widehat{GPA}_i = \hat{\beta}_0 + \hat{\beta}_1 I_i + \hat{\beta}_2 P_i + \hat{\beta}_3 \text{SAT}_i + \hat{\beta}_4 H_i$$

# How?

We estimate the  $\beta$ s with **linear regression**, specifically ordinary least squares

**Ordinary least squares:** choose all the  $\beta$ s so that the sum of squared errors between the *real* GPAs and model-estimated GPAs are minimized:

$$SSE = \sum_{i=1}^N (GPA_i - \widehat{GPA}_i)^2$$

# How?

We estimate the  $\beta$ s with **linear regression**, specifically ordinary least squares

**Ordinary least squares:** choose all the  $\beta$ s so that the sum of squared errors between the *real* GPAs and model-estimated GPAs are minimized:

$$SSE = \sum_{i=1}^N (GPA_i - \widehat{GPA}_i)^2$$

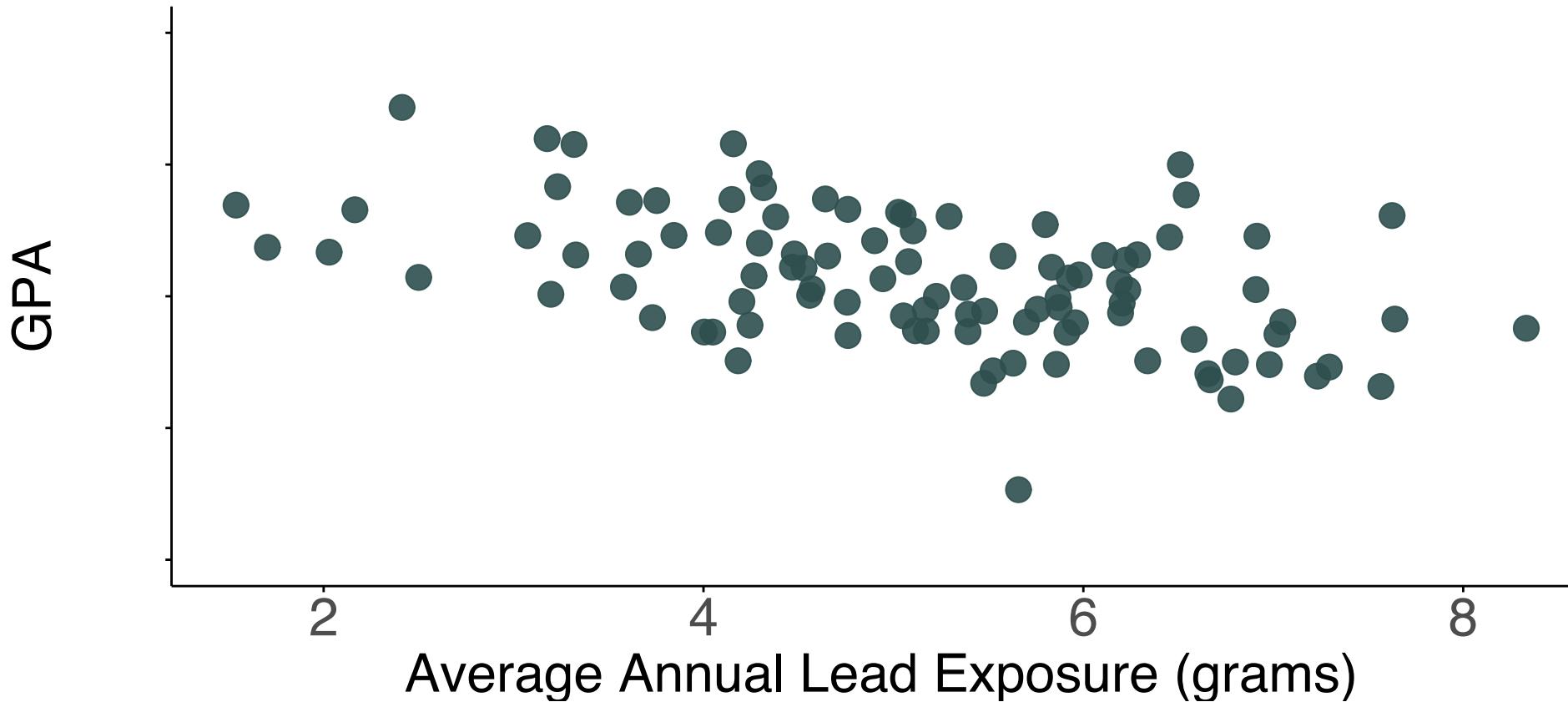
Choosing the  $\beta$ s in this fashion gives us the best-fit line through the data

# How?

# Simple example

Suppose we were only looking at GPA and pollution (lead/Pb):

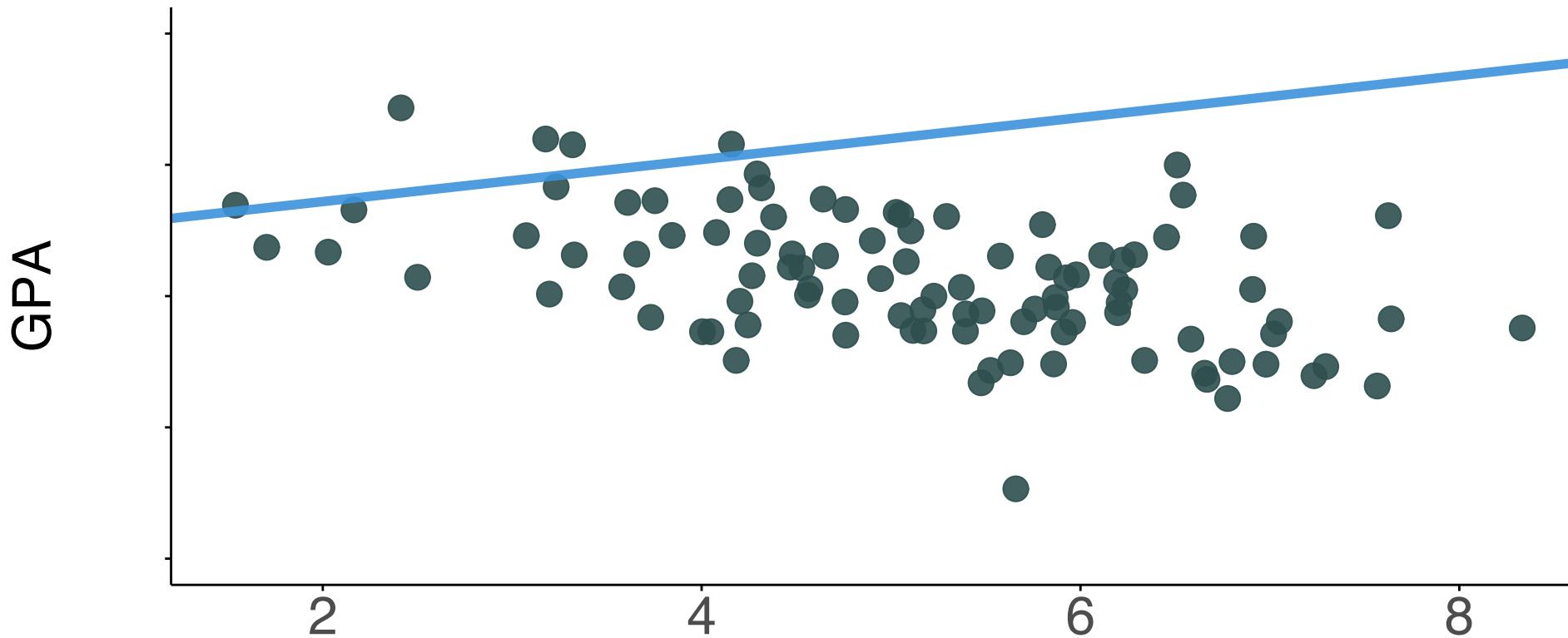
$$\text{GPA}_i = \beta_0 + \beta_1 P_i + \varepsilon_i$$



# Simple example

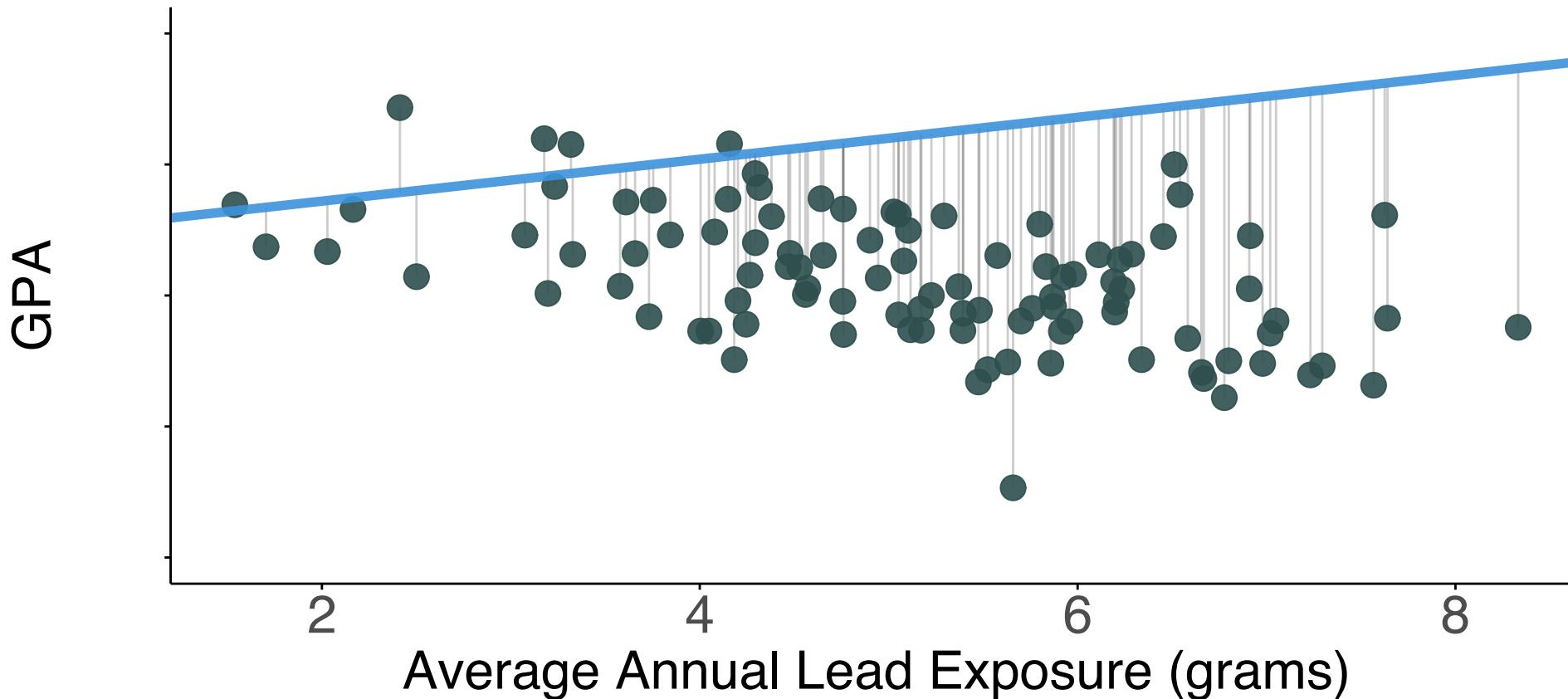
For any line  $(GPA_i = \hat{\beta}_0 + \hat{\beta}_1 P_i)$

```
## Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.  
## i Please use `linewidth` instead.
```



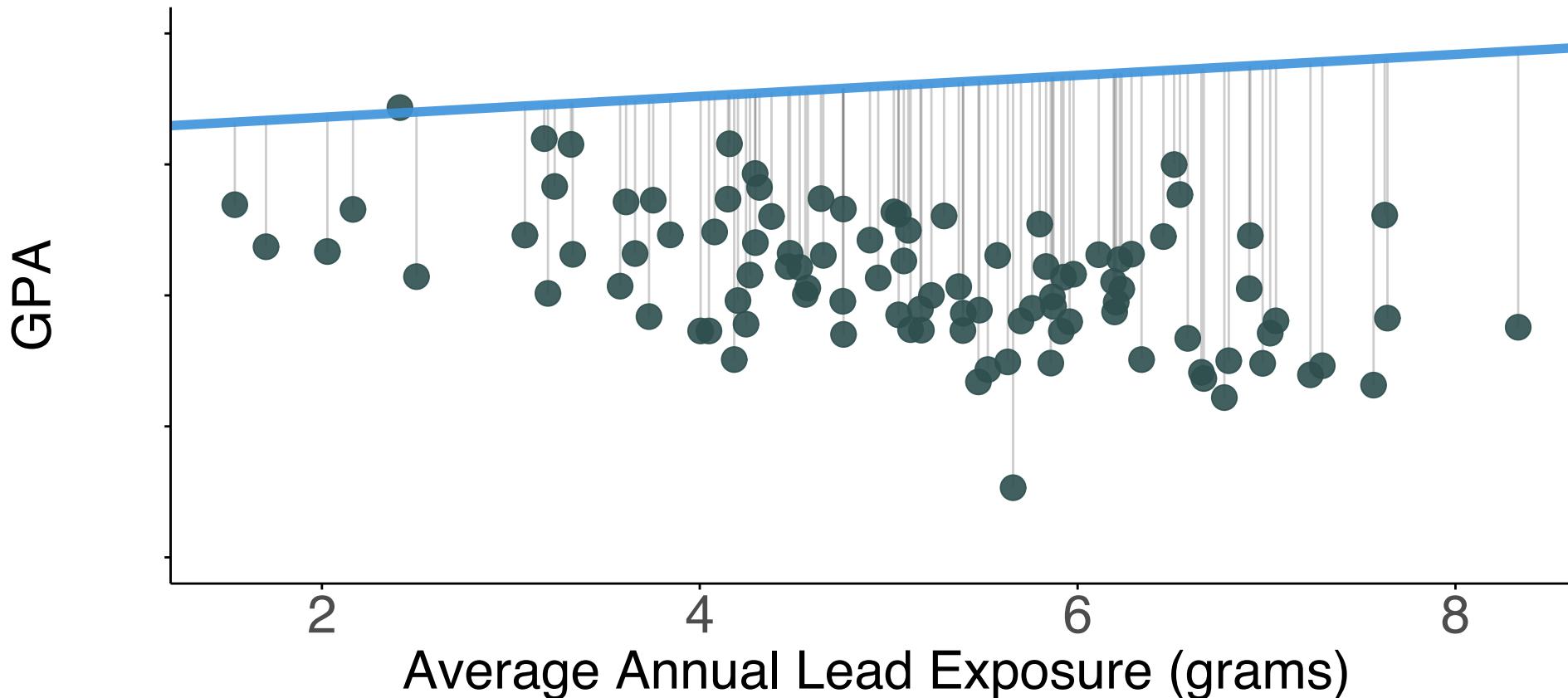
# Simple example

For any line  $(GPA_i = \hat{\beta}_0 + \hat{\beta}_1 P_i)$ , we calculate errors:  $e_i = GPA_i - \hat{GPA}_i$



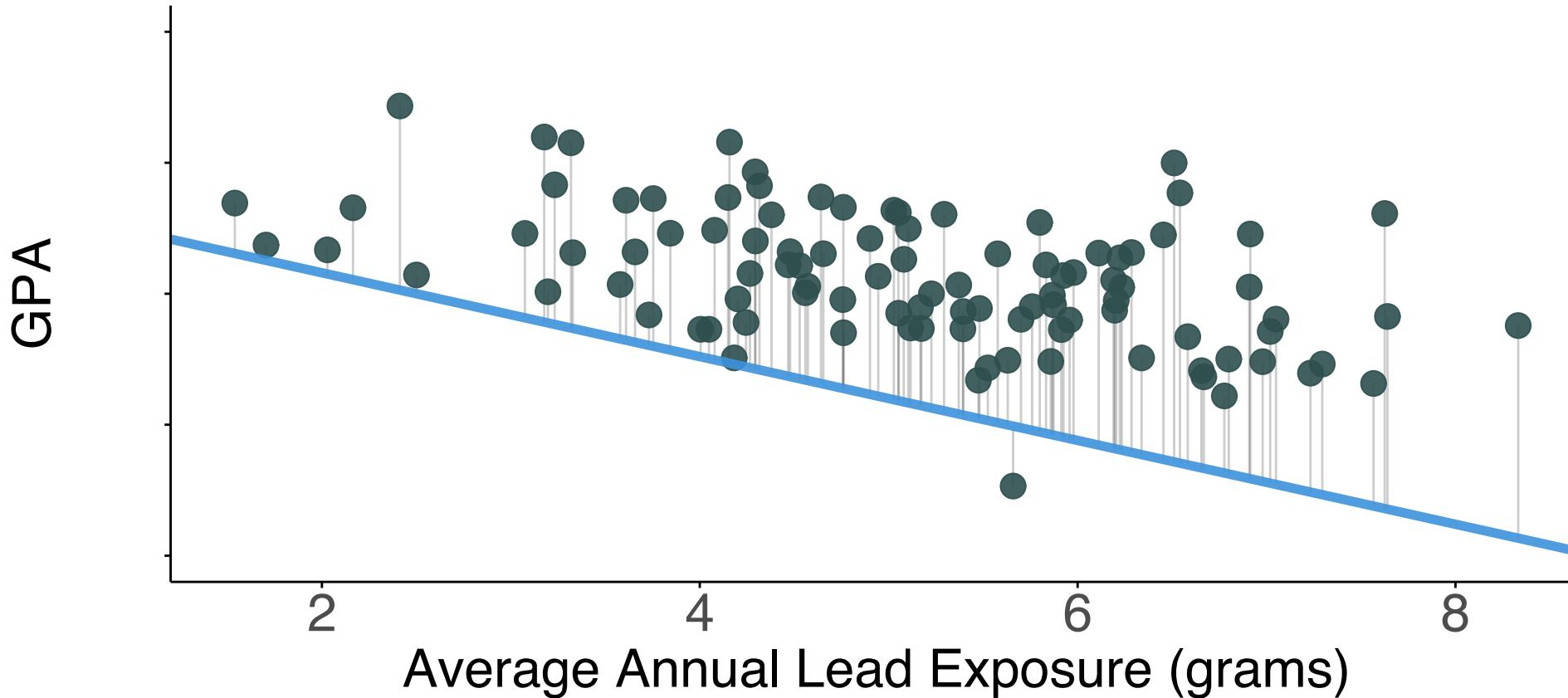
# Simple example

For any line  $(GPA_i = \hat{\beta}_0 + \hat{\beta}_1 P_i)$ , we calculate errors:  $e_i = GPA_i - \hat{GPA}_i$



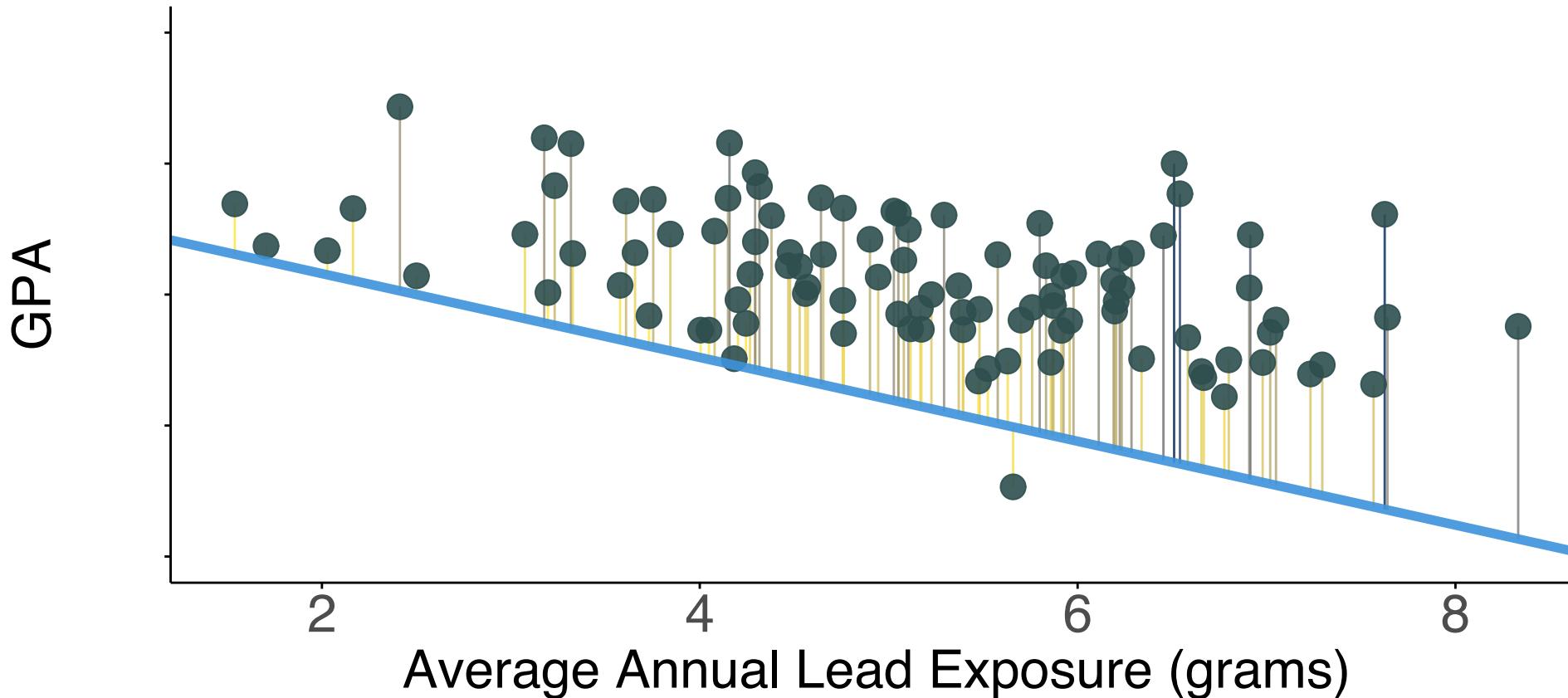
# Simple example

For any line  $(GPA_i = \hat{\beta}_0 + \hat{\beta}_1 P_i)$ , we calculate errors:  $e_i = GPA_i - \hat{GPA}_i$



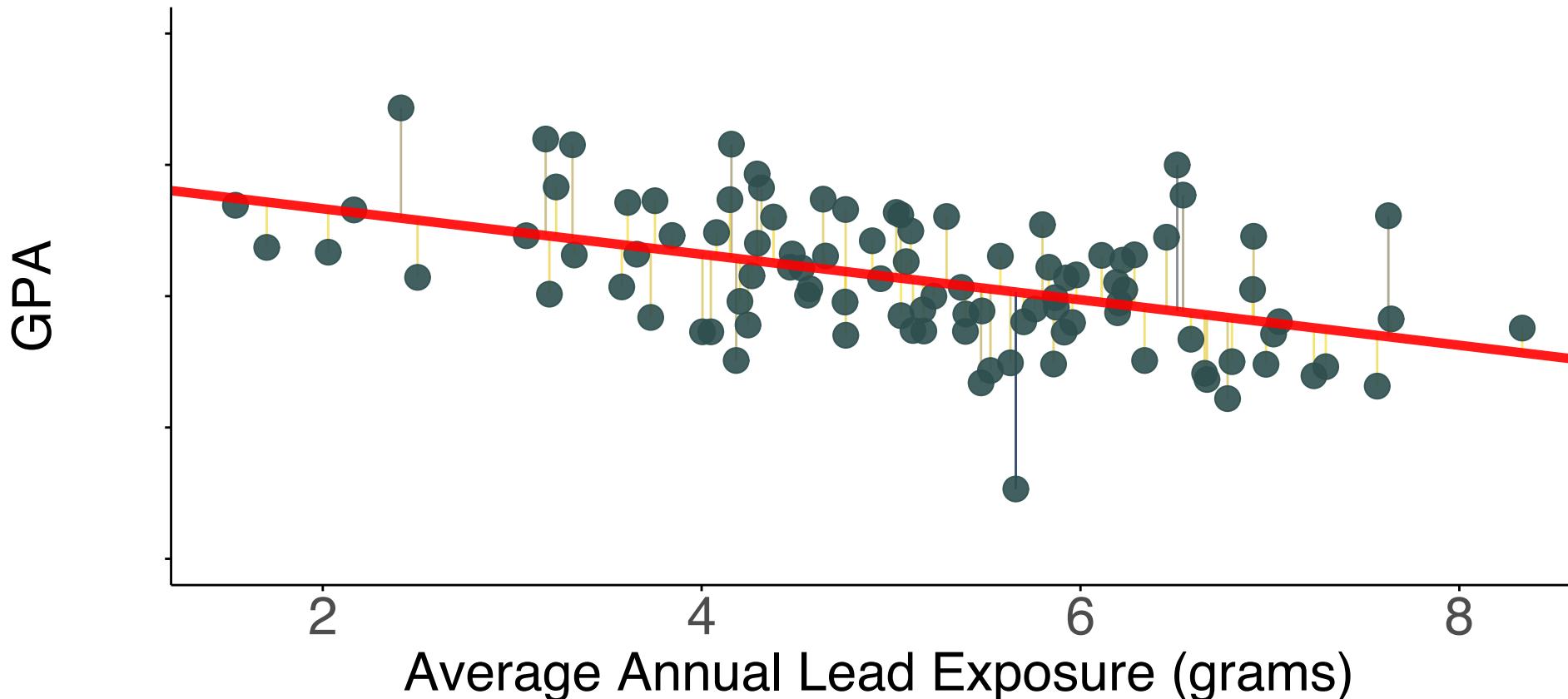
# Simple example

SSE squares the errors ( $\sum e_i^2$ ): bigger errors get bigger penalties



# Simple example

The OLS estimate is the combination of  $\hat{\beta}_0$  and  $\hat{\beta}_1$  that minimize SSE



# OLS error term

So OLS is just the best-fit line through your data

# OLS error term

So OLS is just the best-fit line through your data

# OLS error term

So OLS is just the best-fit line through your data

Why?

# OLS error term

So OLS is just the best-fit line through your data

Why?

Our model isn't perfect, the people in our dataset (i.e. our sample) may not perfectly match up to the entire population of people

# OLS error term

There's **a lot** of other stuff that determines GPAs!

# OLS error term

There's **a lot** of other stuff that determines GPAs!

We jam all that stuff into error term  $\varepsilon_i$ :

$$\text{GPA}_i = \beta_0 + \beta_1 I_i + \beta_2 P_i + \beta_3 \text{SAT}_i + \beta_4 H_i + \varepsilon_i$$

# OLS error term

There's **a lot** of other stuff that determines GPAs!

We jam all that stuff into error term  $\varepsilon_i$ :

$$\text{GPA}_i = \beta_0 + \beta_1 I_i + \beta_2 P_i + \beta_3 \text{SAT}_i + \beta_4 H_i + \varepsilon_i$$

So  $\varepsilon_i$  contains all the determinants of GPA that we aren't explicitly addressing in our model like:

- Home environment
- Time studying

# OLS error term

There's **a lot** of other stuff that determines GPAs!

We jam all that stuff into error term  $\varepsilon_i$ :

$$\text{GPA}_i = \beta_0 + \beta_1 I_i + \beta_2 P_i + \beta_3 \text{SAT}_i + \beta_4 H_i + \varepsilon_i$$

So  $\varepsilon_i$  contains all the determinants of GPA that we aren't explicitly addressing in our model like:

- Home environment
- Time studying

It is just a "catch-all", we don't actually know or see  $\varepsilon_i$

# OLS properties

OLS has one **very** nice property relevant for this class:

# OLS properties

OLS has one **very** nice property relevant for this class:

**Unbiasedness:**  $E[\hat{\beta}] = \beta$

# OLS properties

**Unbiasedness:**  $E[\hat{\beta}] = \beta$

On average, our estimate  $\hat{\beta}$  exactly equals the **true**  $\beta$

# OLS properties

**Unbiasedness:**  $E[\hat{\beta}] = \beta$

On average, our estimate  $\hat{\beta}$  exactly equals the **true**  $\beta$

The key is **on average**: we are estimating our model using only some sample of the data

# OLS properties

**Unbiasedness:**  $E[\hat{\beta}] = \beta$

On average, our estimate  $\hat{\beta}$  exactly equals the **true**  $\beta$

The key is **on average**: we are estimating our model using only some sample of the data

The estimated  $\beta$  won't exactly be right for the entire population, but on average, we expect it to match

# OLS properties

**Unbiasedness:**  $E[\hat{\beta}] = \beta$

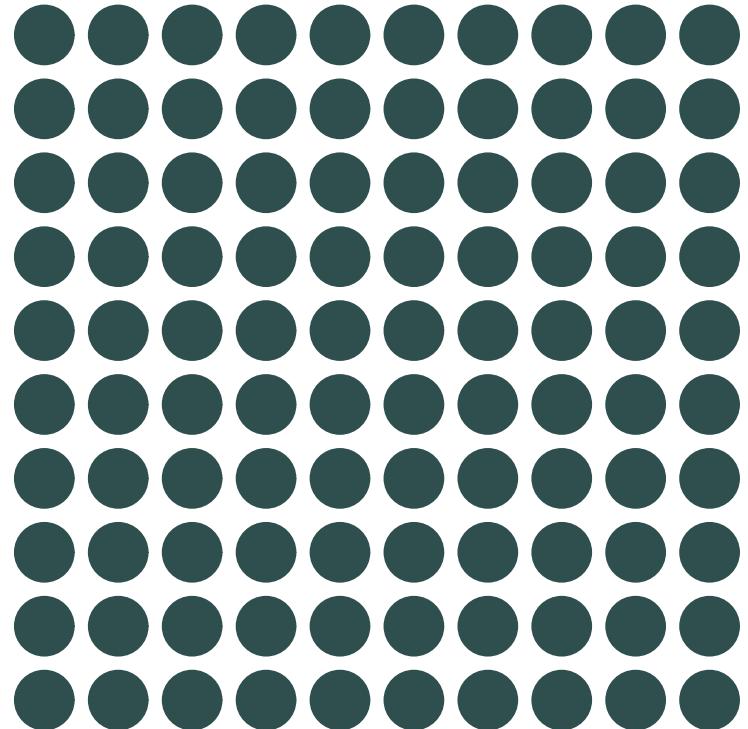
On average, our estimate  $\hat{\beta}$  exactly equals the **true**  $\beta$

The key is **on average**: we are estimating our model using only some sample of the data

The estimated  $\beta$  won't exactly be right for the entire population, but on average, we expect it to match

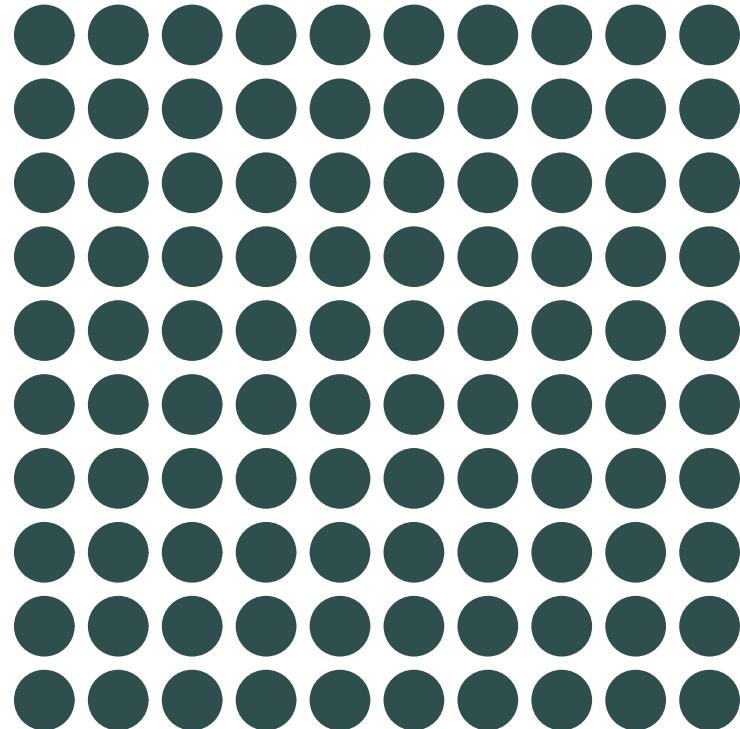
Let's see in an example where we only have a subsample of the full population of data

# OLS properties

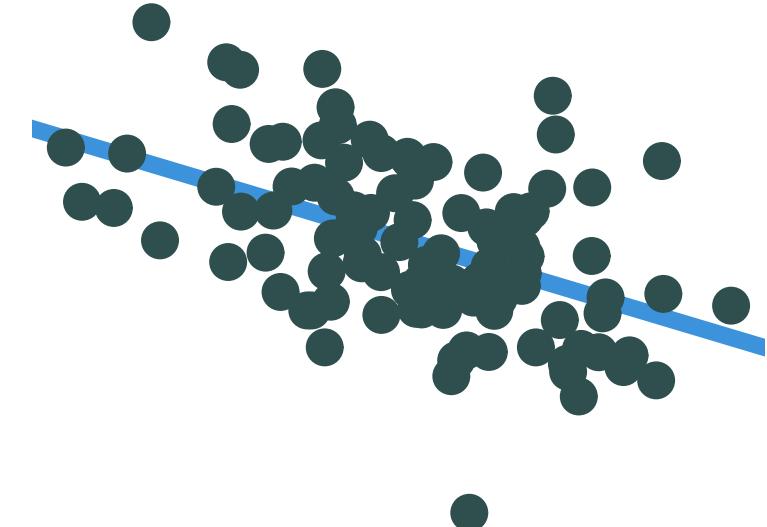


Population

# OLS properties



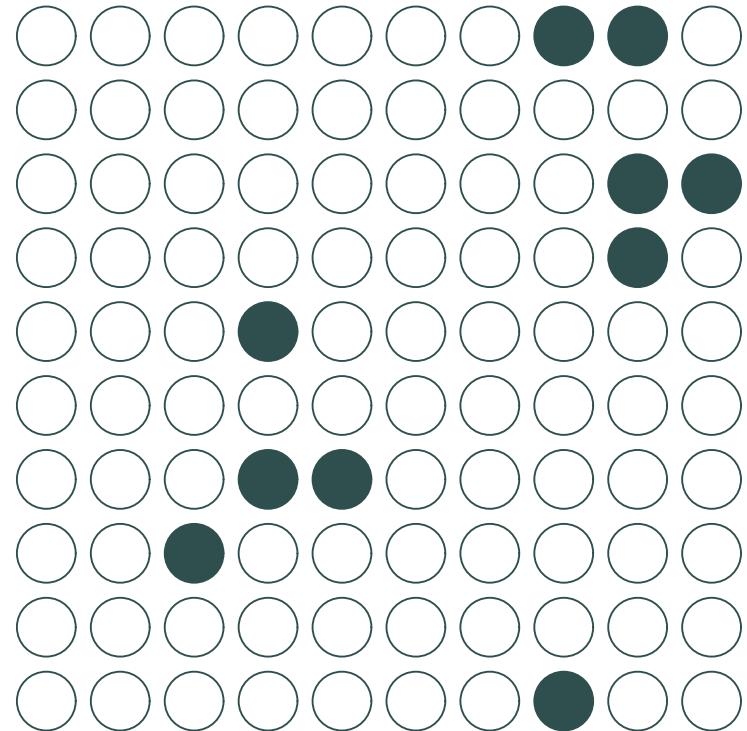
Population



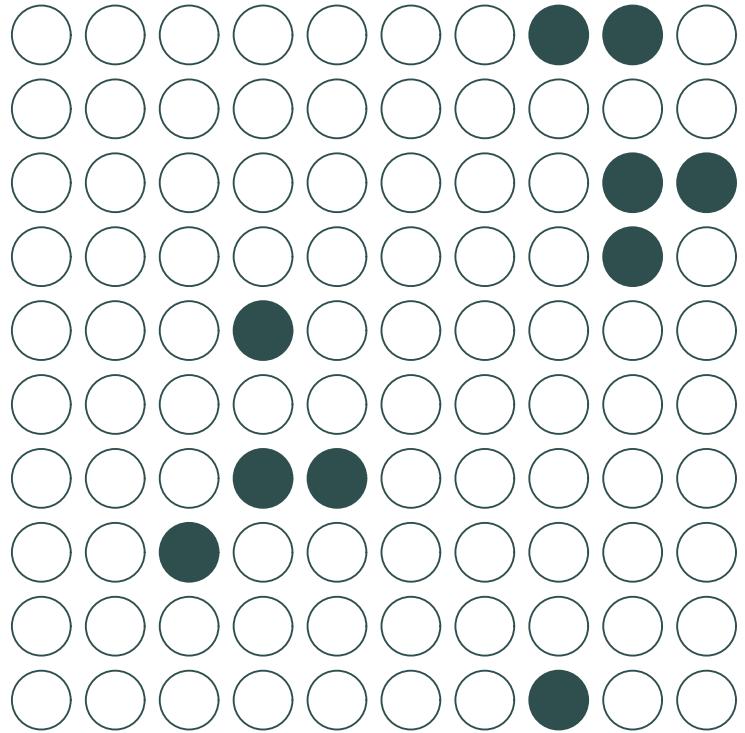
Population relationship

$$y_i = 2.53 + -0.43x_i + u_i$$

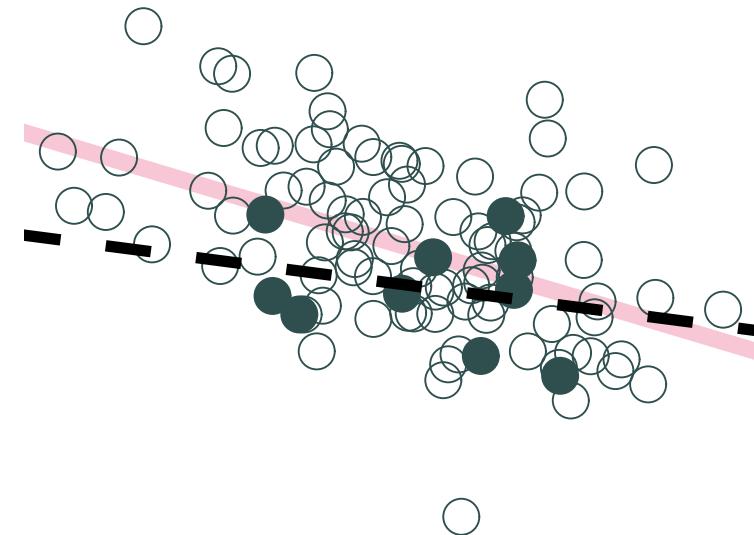
$$y_i = \beta_0 + \beta_1 x_i + u_i$$



**Sample 1:** 10 random individuals



**Sample 1:** 10 random individuals

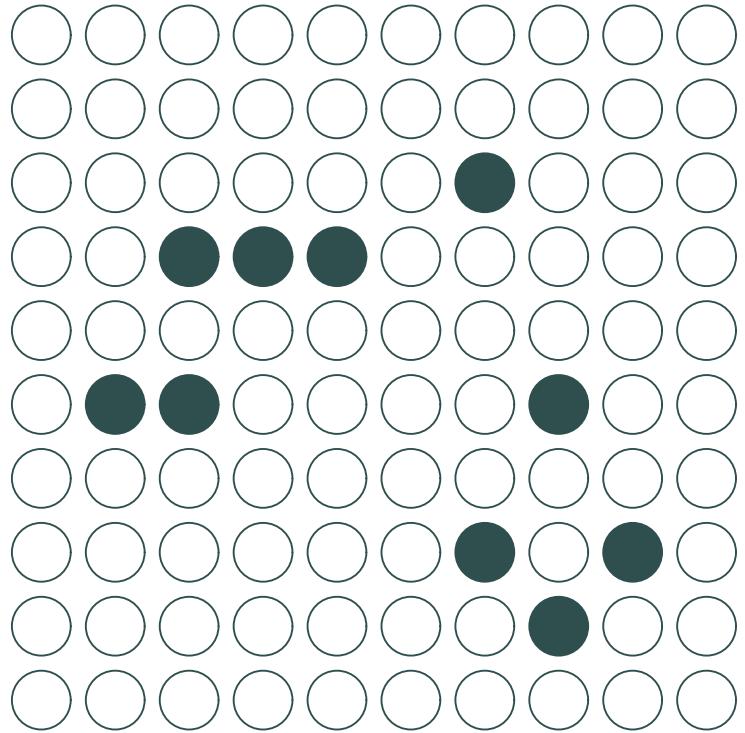


**Population relationship**

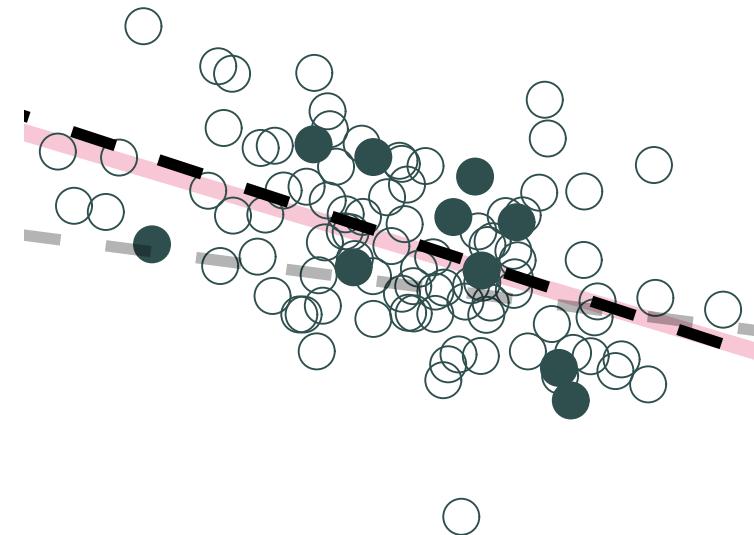
$$y_i = 2.53 + -0.43x_i + u_i$$

**Sample relationship**

$$\hat{y}_i = 0.72 + -0.19x_i$$



**Sample 2:** 10 random individuals

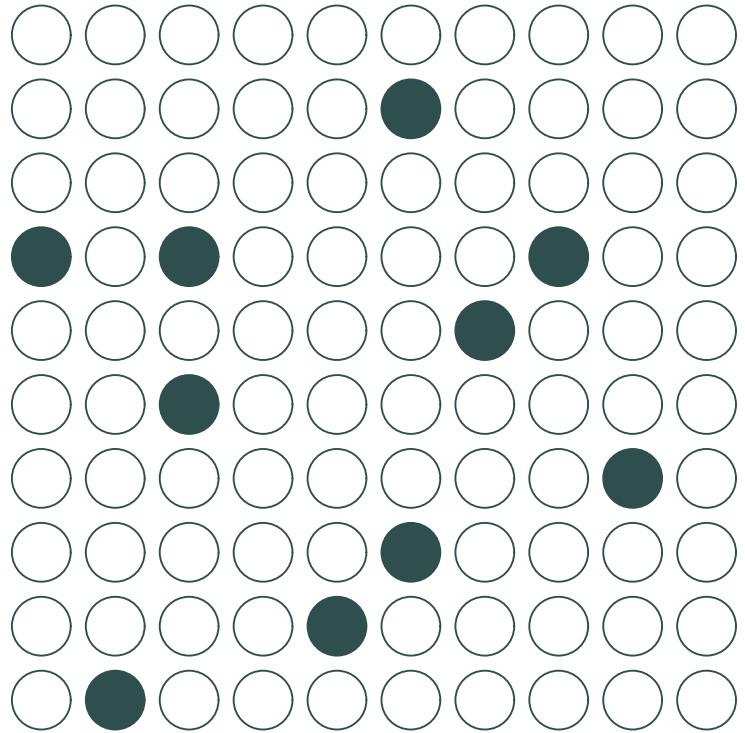


**Population relationship**

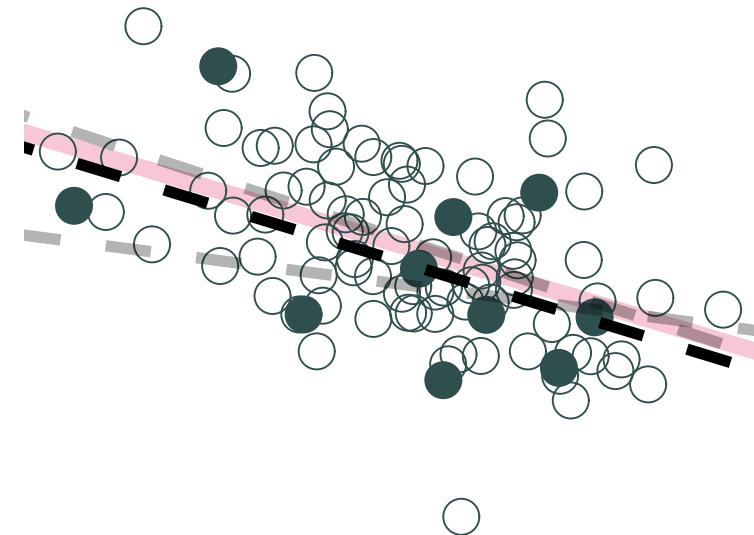
$$y_i = 2.53 + -0.43x_i + u_i$$

**Sample relationship**

$$\hat{y}_i = 2.82 + -0.47x_i$$



**Sample 3:** 10 random individuals



**Population relationship**

$$y_i = 2.53 + -0.43x_i + u_i$$

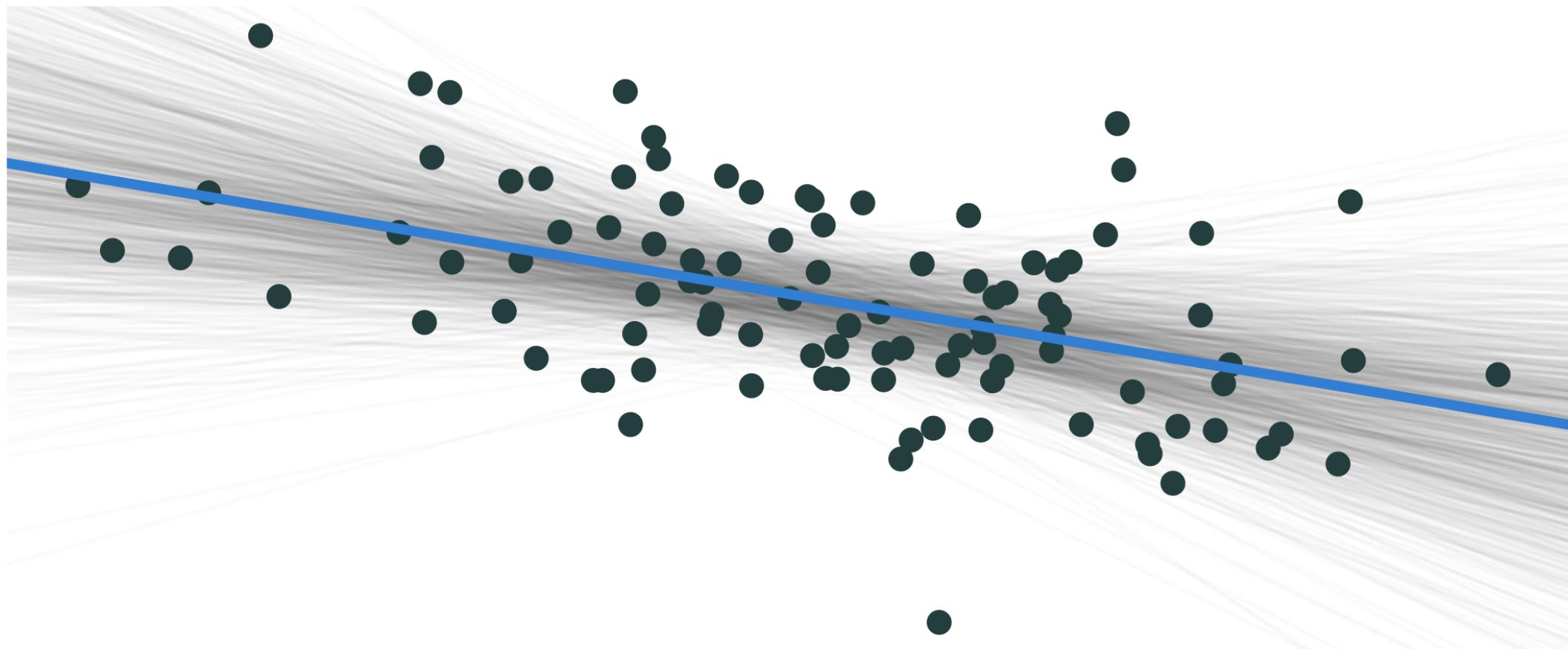
**Sample relationship**

$$\hat{y}_i = 2.32 + -0.44x_i$$

**Let's repeat this 1,000 times.**

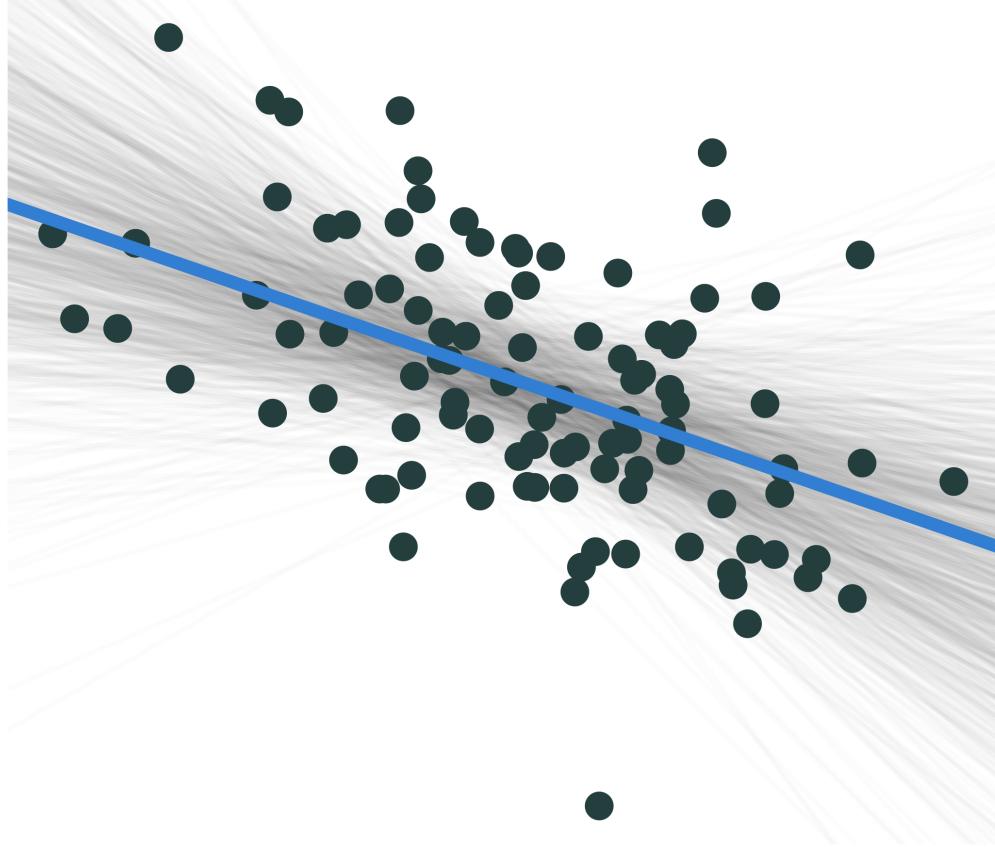
(This exercise is called a (Monte Carlo) simulation.)

# Population vs. sample



# Population vs. sample

**Question:** Why do we care about *population* vs. *sample*?



On **average**, our regression lines match the population line very nicely

However, **individual lines** (samples) can really miss the mark

# Population vs. sample

**Answer:** Uncertainty/randomness matters!

# Population vs. sample

**Answer:** Uncertainty/randomness matters!

$\hat{\beta}$  itself is will depend on the sample of data we have

# Population vs. sample

**Answer:** Uncertainty/randomness matters!

$\hat{\beta}$  itself is will depend on the sample of data we have

When we take a sample and run a regression, we don't know if it's a 'good' sample ( $\hat{\beta}$  is close to  $\beta$ ) or a 'bad sample' (our sample differs greatly from the population)

# Unbiasedness

For OLS to be unbiased and give us, on average, the causal effect of some  $X$  on some  $Y$  we need a few assumptions to hold

# Unbiasedness

For OLS to be unbiased and give us, on average, the causal effect of some X on some Y we need a few assumptions to hold

Whether or not these assumptions are true is why you often hear *correlation is not causation*

# Unbiasedness

For OLS to be unbiased and give us, on average, the causal effect of some X on some Y we need a few assumptions to hold

Whether or not these assumptions are true is why you often hear *correlation is not causation*

If we want some  $\hat{\beta}_1$  on a variable  $x$  to be unbiased we  $x$  to be **uncorrelated** with the error term:

$$E[x\varepsilon] = 0 \quad \leftrightarrow \quad \text{correlation}(x, \varepsilon) = 0$$

# Unbiasedness

The variable you are interested in **cannot** be correlated with the error term

# Unbiasedness

The variable you are interested in **cannot** be correlated with the error term

What does this mean in words?

# Unbiasedness

The variable you are interested in **cannot** be correlated with the error term

What does this mean in words?

The error term contains all variables that determine  $y$ , but we *omitted* from our model

# Unbiasedness

The variable you are interested in **cannot** be correlated with the error term

What does this mean in words?

The error term contains all variables that determine  $y$ , but we *omitted* from our model

We are assuming that our variable of interest,  $x$ , is not correlated with any of these omitted variable

# Unbiasedness

The variable you are interested in **cannot** be correlated with the error term

What does this mean in words?

The error term contains all variables that determine  $y$ , but we *omitted* from our model

We are assuming that our variable of interest,  $x$ , is not correlated with any of these omitted variable

If  $x$  is correlated with any of them, then we will have something called **omitted variable bias**

# Omitted variable bias

Here's an intuitive example

# Omitted variable bias

Here's an intuitive example

Suppose we wanted to understand the effect of lead exposure  $P$  on GPAs

# Omitted variable bias

Here's an intuitive example

Suppose we wanted to understand the effect of lead exposure  $P$  on GPAs

lead harms children's brain development, especially before age 6

# Omitted variable bias

Here's an intuitive example

Suppose we wanted to understand the effect of lead exposure  $P$  on GPAs

lead harms children's brain development, especially before age 6

We should expect early-life lead exposure to reduce future GPAs

# Omitted variable bias

Our model might look like:

$$\text{GPA}_i = \beta_0 + \beta_1 \text{P}_i + \varepsilon_i$$

# Omitted variable bias

Our model might look like:

$$\text{GPA}_i = \beta_0 + \beta_1 \text{P}_i + \varepsilon_i$$

We want to know  $\beta_1$

# Omitted variable bias

Our model might look like:

$$\text{GPA}_i = \beta_0 + \beta_1 \text{P}_i + \varepsilon_i$$

We want to know  $\beta_1$

What would happen if we took a sample of *real world data* and used OLS to estimate  $\hat{\beta}_1$ ?

# Omitted variable bias

We would have omitted variable bias

# Omitted variable bias

We would have omitted variable bias

Why? What are some examples?

# Omitted variable bias

We would have omitted variable bias

Why? What are some examples?

**Who** is more likely to be exposed to lead?

# Omitted variable bias

We would have omitted variable bias

Why? What are some examples?

**Who** is more likely to be exposed to lead?

Poorer families likely have more lead exposure, why?

# Omitted variable bias

We would have omitted variable bias

Why? What are some examples?

**Who** is more likely to be exposed to lead?

Poorer families likely have more lead exposure, why?

Richer families can move away, pay to replace lead paint, lead pipes, etc

# Omitted variable bias

We would have omitted variable bias

Why? What are some examples?

**Who** is more likely to be exposed to lead?

Poorer families likely have more lead exposure, why?

Richer families can move away, pay to replace lead paint, lead pipes, etc

This means lead exposure is correlated with lower income

# Omitted variable bias

Why does this correlation cause us problems?

# Omitted variable bias

Why does this correlation cause us problems?

Family income *also* matters for GPA, it is in  $\varepsilon_i$ , so our assumption that  $\text{correlation}(x, \varepsilon) = 0$  is violated

# Omitted variable bias

Why does this correlation cause us problems?

Family income *also* matters for GPA, it is in  $\varepsilon_i$ , so our assumption that  $\text{correlation}(x, \varepsilon) = 0$  is violated

Children from richer families tend to have higher GPAs

# Omitted variable bias

Why does this correlation cause us problems?

Family income *also* matters for GPA, it is in  $\varepsilon_i$ , so our assumption that  $\text{correlation}(x, \varepsilon) = 0$  is violated

Children from richer families tend to have higher GPAs

Why?

# Omitted variable bias

Why does this correlation cause us problems?

Family income *also* matters for GPA, it is in  $\varepsilon_i$ , so our assumption that  $\text{correlation}(x, \varepsilon) = 0$  is violated

Children from richer families tend to have higher GPAs

Why?

Access to tutoring, better schools, parental pressure, etc, etc

# Omitted variable bias

If we just look at the effect of lead exposure on GPAs without addressing its correlation with income, lead exposure will look worse than it actually is

# Omitted variable bias

If we just look at the effect of lead exposure on GPAs without addressing its correlation with income, lead exposure will look worse than it actually is

This is because our data on lead exposure is also proxying for income (since  $\text{correlation}(x, \varepsilon) = 0$ )

# Omitted variable bias

If we just look at the effect of lead exposure on GPAs without addressing its correlation with income, lead exposure will look worse than it actually is

This is because our data on lead exposure is also proxying for income (since  $\text{correlation}(x, \varepsilon) = 0$ )

So  $\hat{\beta}_1$  will pick up the effect of both!

# Omitted variable bias

If we just look at the effect of lead exposure on GPAs without addressing its correlation with income, lead exposure will look worse than it actually is

This is because our data on lead exposure is also proxying for income (since  $\text{correlation}(x, \varepsilon) = 0$ )

So  $\hat{\beta}_1$  will pick up the effect of both!

Our estimate  $\hat{\beta}_1$  is **biased** and overstates the negative effects of lead

# Omitted variable bias

How do we fix this bias?

# Omitted variable bias

How do we fix this bias?

Make income not omitted: control for it in our model

# Omitted variable bias

How do we fix this bias?

Make income not omitted: control for it in our model

If we have data on family income  $I$  we can instead write our model as:

$$\text{GPA}_i = \beta_0 + \beta_1 P_i + \beta_2 I_i + \varepsilon_i$$

$I$  is no longer omitted

# Omitted variable bias

How do we fix this bias?

Make income not omitted: control for it in our model

If we have data on family income  $I$  we can instead write our model as:

$$\text{GPA}_i = \beta_0 + \beta_1 P_i + \beta_2 I_i + \varepsilon_i$$

$I$  is no longer omitted

Independent variables in our model that we include to address bias are called  
**controls**

# Hands-on pollution education example

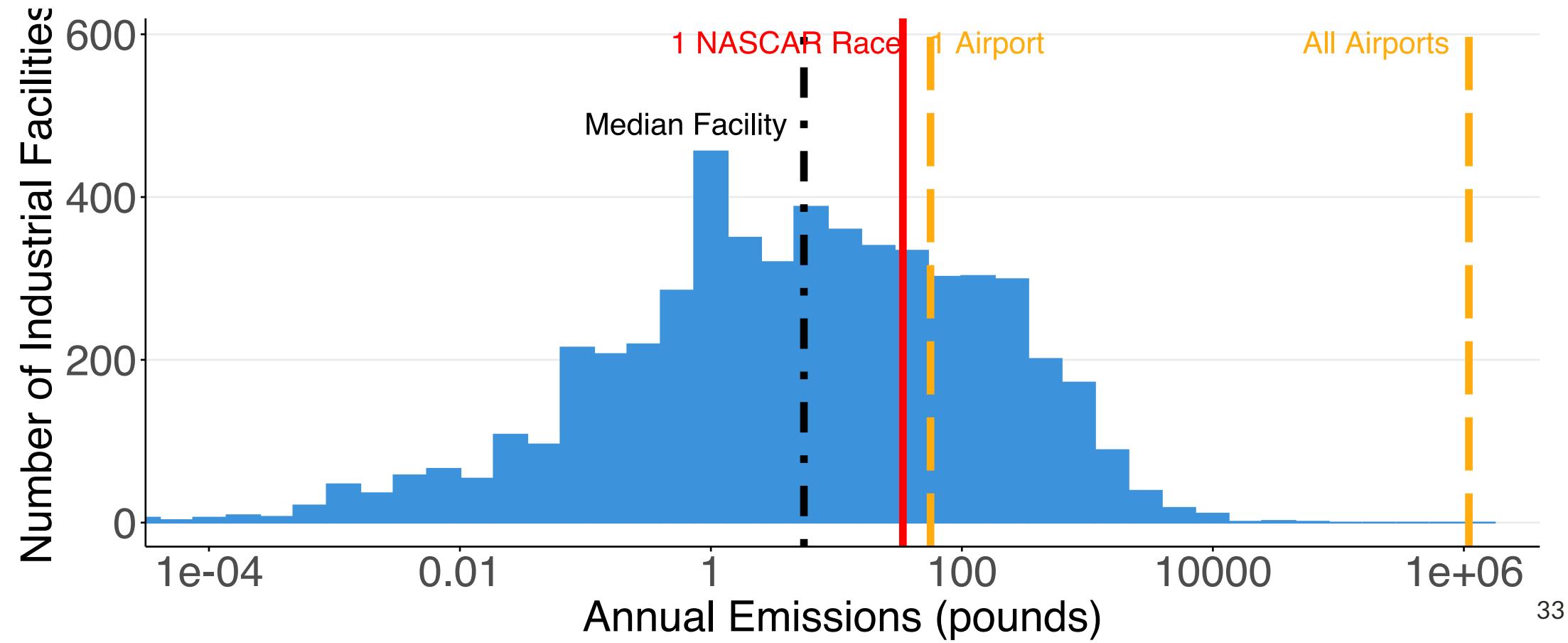
---

# Real pollution education example



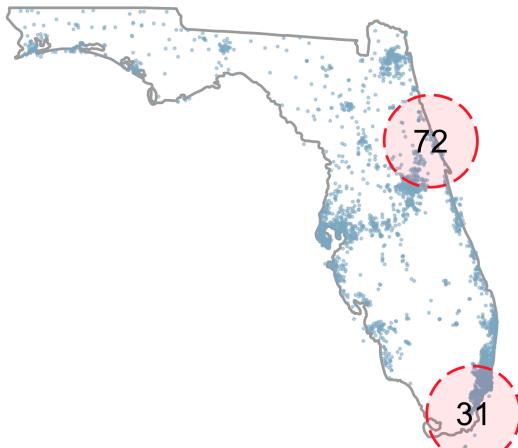
# Real pollution education example

In **3 hours**, one NASCAR race emits more lead than a majority of industrial facilities do in an **entire year**



# We will look at Florida

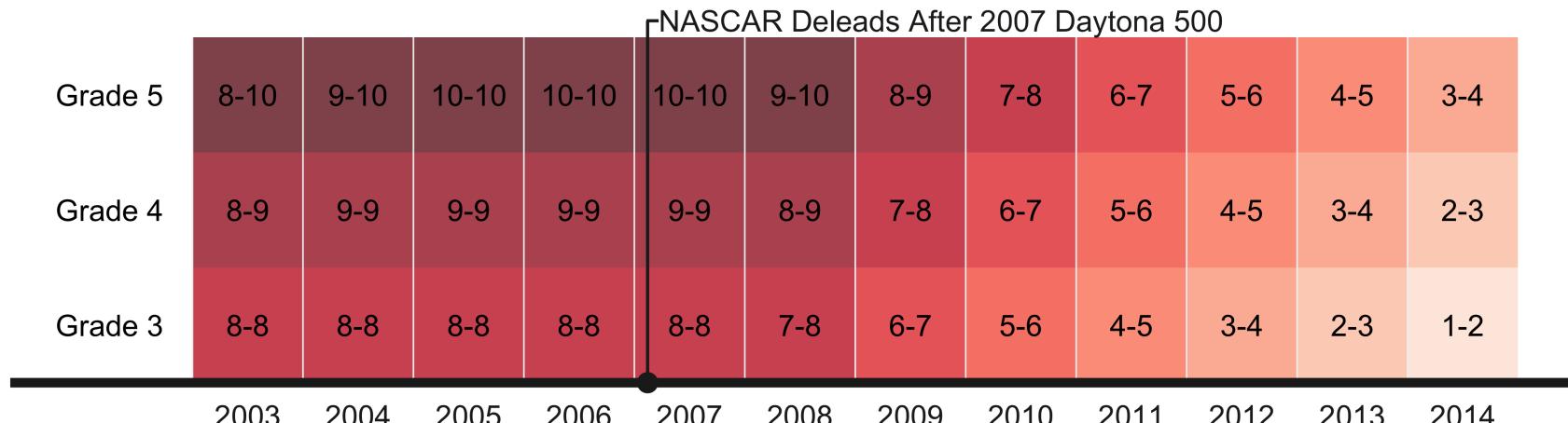
A. Track and School Locations



B. Time Series of Lead Exposure from NASCAR



C. Range of Total Years Exposed to NASCAR Lead By Grade and Year



# All the data are public, you can look at scores yourself!



FLORIDA DEPARTMENT OF  
**EDUCATION**  
fldoe.org

[Home](#) | [About Us](#) | [Newsroom](#) | [How Do I?](#) | [Contact Us](#) | [Public Records](#)

AAA

What are you looking for?



FEATURED TOPICS

ACADEMICS

SCHOOLS

TEACHING

ACCOUNTABILITY

POLICY

FINANCE

[Home](#) | [Accountability](#) | [Assessments](#) | [K-12 Student Assessment](#) | [Assessments & Publications Archive](#) | [FCAT Historical](#) | [Scores & Reports](#)

## Scores & Reports

[2003 Score Reports](#)

[2004 Score Reports](#)

[2005 Score Reports](#)

[2006 Score Reports](#)

[2007 Score Reports](#)

[2008 Score Reports](#)

[2009 Score Reports](#)

[2010 Score Reports](#)

## Scores & Reports

For results by reporting year, use the link for the appropriate year in the left-hand navigation panel. For results by subject area (e.g., reading, science), use one of the links below. [FCAT 2.0 results](#) are also available, and the [interactive reporting](#) resources provide access to databases that allow users to generate reports for the state, districts or schools for certain educational areas.

- [FCAT Reading & Mathematics SSS Scores \(1998-2011\)](#)
- [FCAT Science SSS Scores \(2003-2011\)](#)
- [FCAT Writing Scores \(1997-2012\)](#)
- [FCAT Norm-Referenced Test Scores \(1995-2008\)](#)
- [Longitudinal Data: FWAP / FCAT / HSCT 1995-2000](#)

## Additional Resources for Understanding Results

- [Understanding FCAT Reports](#)
- [FCAT Achievement Level Definitions/Tables \(PDF\)](#)
- [Developmental Score Scale Memo \(04/14/02\) \(PDF\)](#)
- [Guidance on Content Area Scores](#)
- [Content Focus Reports](#)

# Let's look at the data

```
nascar_df
```

```
## # A tibble: 68,858 × 12
##   school_id school_name grade year zscore nascar_lead nascar_lead_weighted years_leaded indust...¹
##   <dbl> <chr>     <dbl> <dbl> <dbl>       <dbl>                 <dbl>           <dbl>      <dbl>
## 1       56 HAMILTON ELEM     3 2003 -0.186      72.2                2.53        8 822328.
## 2       56 HAMILTON ELEM     4 2003  0.101      80.4                2.81        8 822639.
## 3       56 HAMILTON ELEM     5 2003 -0.206      88.0                3.08        8 822909.
## 4       56 HAMILTON ELEM     3 2004 -0.686      74.0                2.59        8 967077.
## 5       56 HAMILTON ELEM     4 2004 -0.633      82.4                2.88        8 967352.
## 6       56 HAMILTON ELEM     5 2004  0.352      90.5                3.17        8 967663.
## 7       56 HAMILTON ELEM     3 2005 -1.14       77.0                2.69        8 1061570.
## 8       56 HAMILTON ELEM     4 2005 -0.649      84.7                2.97        8 1062071.
## 9       56 HAMILTON ELEM     5 2005 -0.336      92.0                3.26        8 1062346.
## 10      56 HAMILTON ELEM    3 2006 -0.333      79.9                2.80        8 1164072.
## # ... with 68,848 more rows, and abbreviated variable names ¹industrial_lead, ²median_income, ³unemp_n
```

# My sister is in these observations!

```
nascar_df |> # only keep Saturn Elementary School  
  filter(school_name == "SATURN ELEM")
```

```
## # A tibble: 21 × 12  
##   school_id school_name grade year  zscore nascar_lead nascar_lead_weighted years_leaded indust...1  
##   <dbl> <chr>      <dbl> <dbl>    <dbl>        <dbl>                <dbl>          <dbl>       <dbl>  
## 1     2067 SATURN ELEM     3  2003    0.105         0                  0           0          0  823844.  
## 2     2067 SATURN ELEM     4  2003   -0.0633        0                  0           0          0  824155.  
## 3     2067 SATURN ELEM     5  2003    0.163         0                  0           0          0  824425.  
## 4     2067 SATURN ELEM     3  2004    0.655         0                  0           0          0  967646.  
## 5     2067 SATURN ELEM     4  2004    0.586         0                  0           0          0  967921.  
## 6     2067 SATURN ELEM     5  2004    0.679         0                  0           0          0  968232.  
## 7     2067 SATURN ELEM     3  2005    1.03          0                  0           0          0 1059953.  
## 8     2067 SATURN ELEM     4  2005    0.131         0                  0           0          0 1060454.  
## 9     2067 SATURN ELEM     5  2005    0.696         0                  0           0          0 1060729.  
## 10    2067 SATURN ELEM     3  2006    0.599         0                  0           0          0 1161336.  
## # ... with 11 more rows, and abbreviated variable names 1industrial_lead, 2median_income, 3unemp_rate,
```

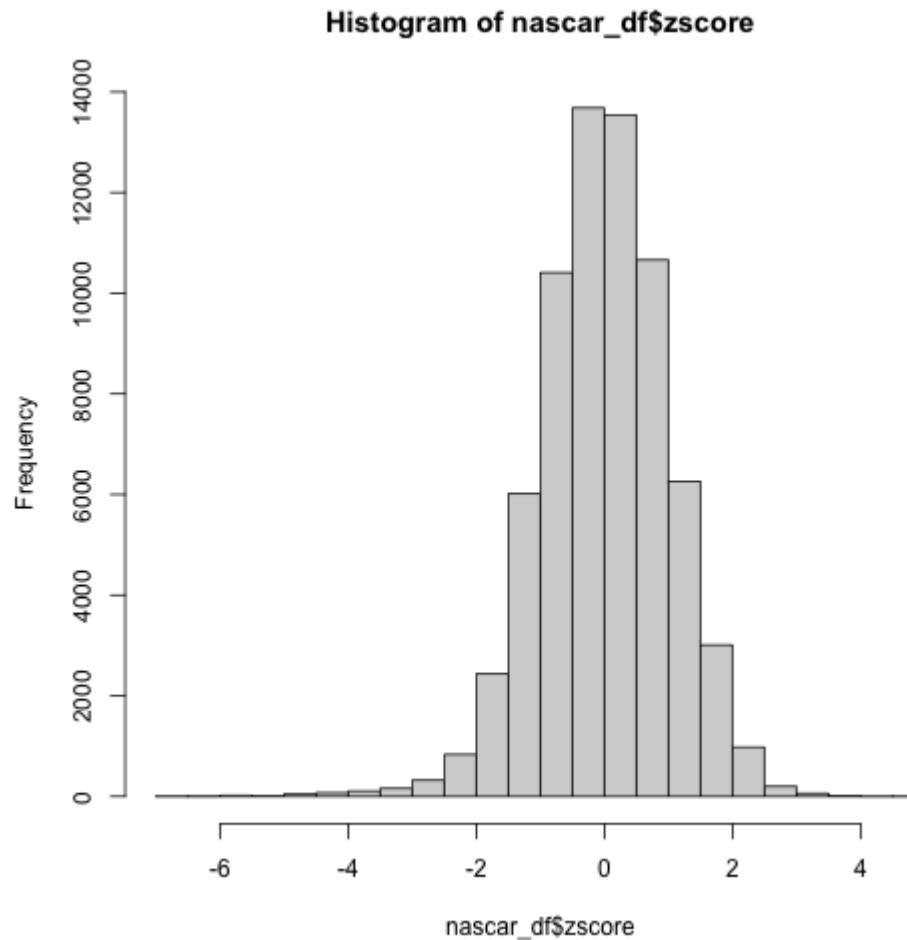
# Let's look at the data

```
##   school_id      zscore      nascar_lead    industrial_lead median_income num_students
## Min.   : 3   Min.   :-6.765987   Min.   : 0.00   Min.   :     0   Min.   :25201   Min.   : 10.0
## 1st Qu.: 961  1st Qu.:-0.630857  1st Qu.: 0.00   1st Qu.: 300489  1st Qu.:41184   1st Qu.: 72.0
## Median :1811  Median : 0.012807  Median : 0.00   Median : 562856  Median :44635   Median :100.0
## Mean   :1832  Mean   : 0.000358  Mean   :12.88   Mean   :1197073  Mean   :44712   Mean   :102.5
## 3rd Qu.:2702  3rd Qu.: 0.661761  3rd Qu.:16.38   3rd Qu.:2040709  3rd Qu.:48772   3rd Qu.:130.0
## Max.   :4110  Max.   : 4.884255  Max.   :92.02   Max.   :6454837  Max.   :67238   Max.   :447.0
```

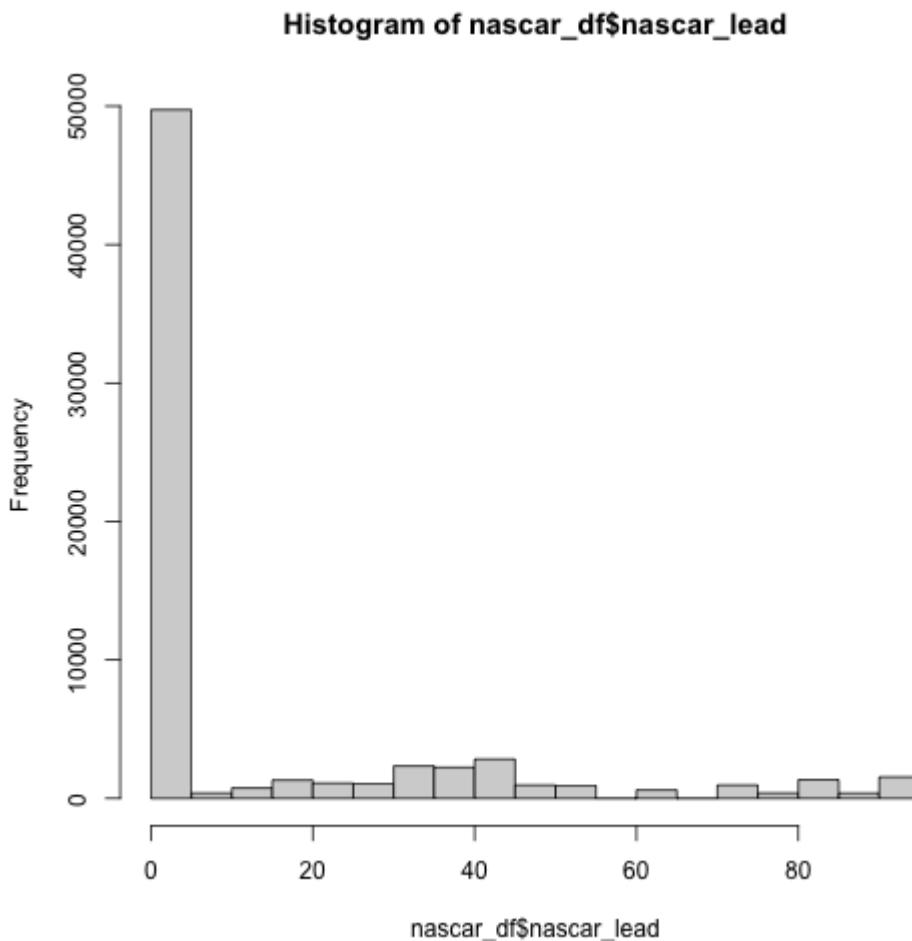
# The variables

- **zscore**: the school's score for the average student in terms of standard deviations above or below the state-wide average
- **nascar lead**: lifetime exposure to lead emissions from NASCAR tracks within 50 miles
- **industrial lead**: lead emissions from industrial sources (e.g. factories) within 50 miles
- **median income**: the school district's median income
- **num students**: the number of students at the school
- **school id, school name, grade, and year**: self-explanatory

# What does the distribution of scores look like?



# What about exposure to NASCAR lead

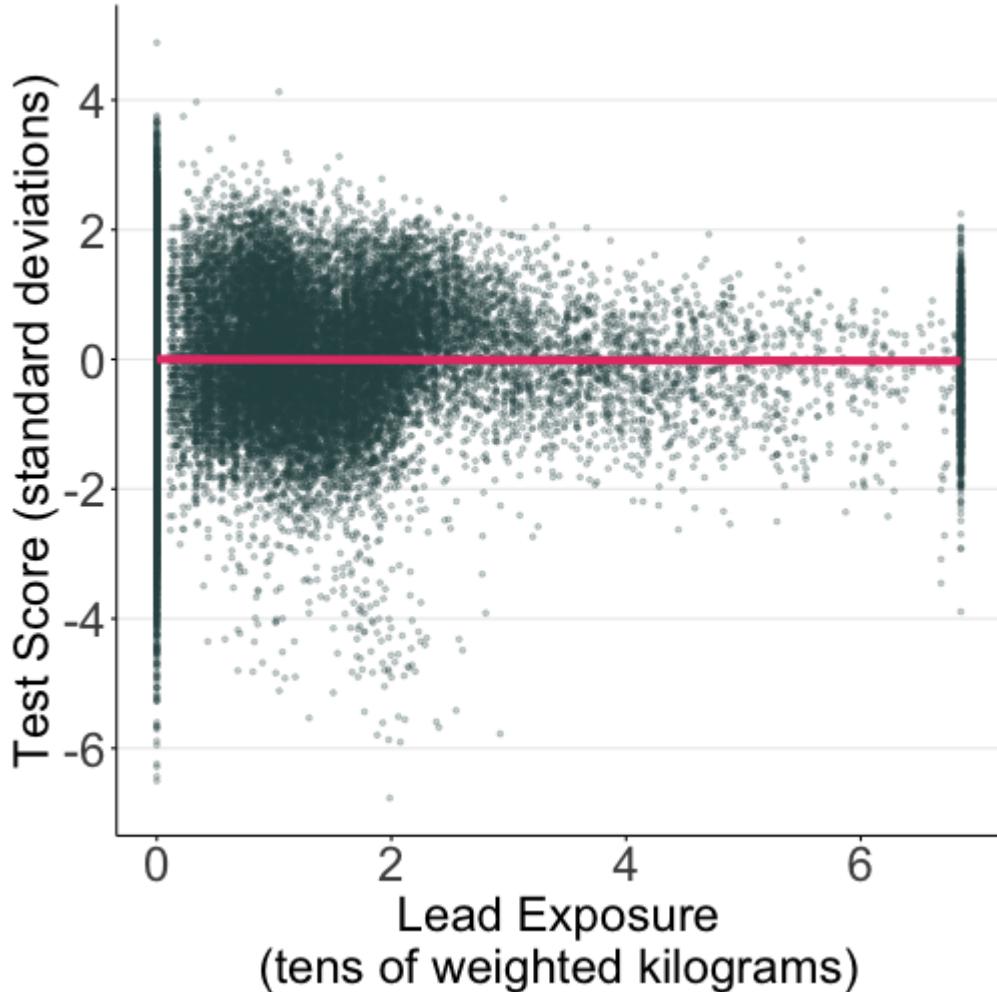


Most schools have zero exposure

Some have a lot

Units are 10s of kilograms

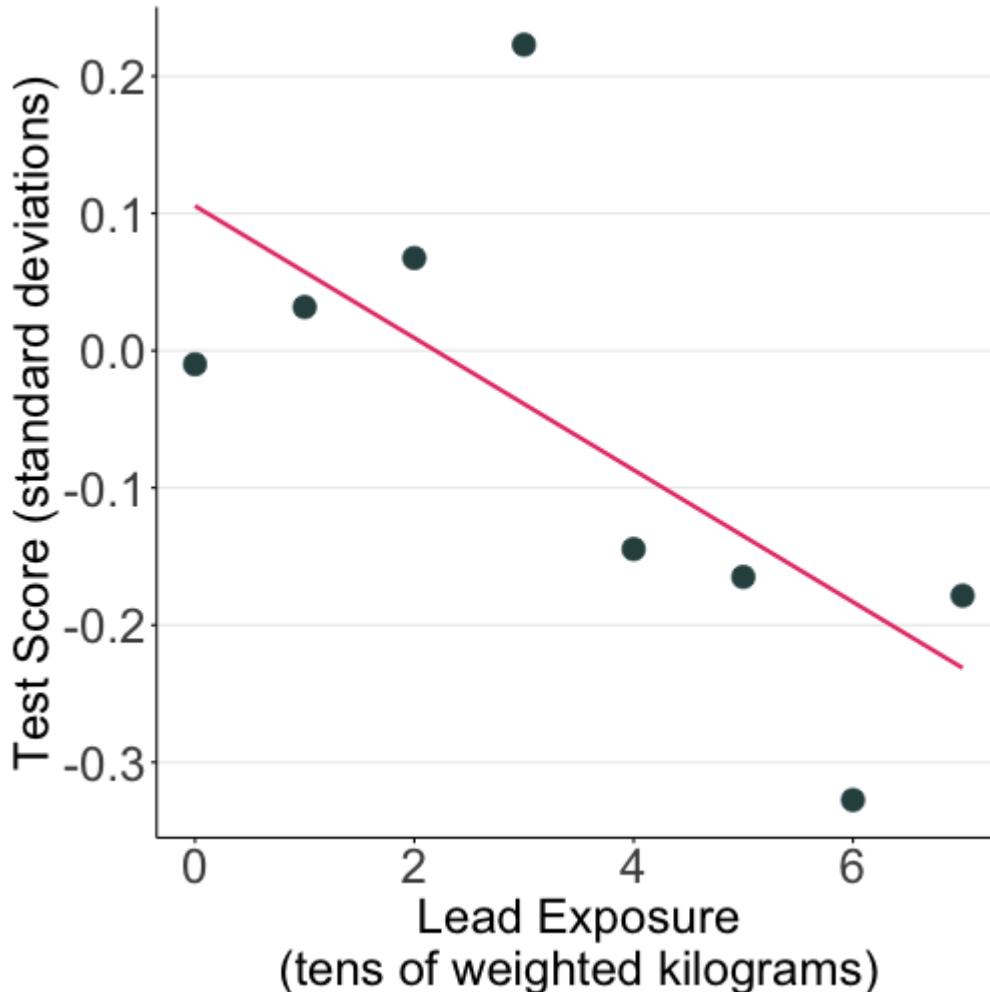
# What is the association between lead and scores?



Let's look at the pure correlation  
between test scores and lead

There's a lot of data so it's kind of  
hard to see but it appears there's a  
**negative** association: lead is bad for  
test scores

# What is the association between lead and scores?



Lets **bin** the data to see the pattern more clearly

All I'm doing is:

- Rounding lead to the nearest integer
- Taking the average of test scores for that bin
- Plot the average scores versus rounded lead

# What is the association between lead and scores?

We can get a better sense by running a regression:

$$zscore_{sgy} = \beta_0 + \beta_1 nascar\_lead\_weighted_{sgy}$$

( $s$  is school,  $g$  is grade,  $y$  is year)

# What is the association between lead and scores?

```
## Estimation Results
##   parameter           estimate
## 1 beta_0  (Intercept)    0.002
## 2 beta_1 nascar_lead_weighted -0.004
```

What does this mean?

An additional 10 kg of lead exposure is associated with a school having an average test score 0.004 standard deviations lower

# Do we believe this number?

What's a potential issue with just looking at the raw association?

# Do we believe this number?

What's a potential issue with just looking at the raw association?

Schools near NASCAR tracks are probably a lot different than schools further away

# Do we believe this number?

What's a potential issue with just looking at the raw association?

Schools near NASCAR tracks are probably a lot different than schools further away

We want to control for things that are potentially correlated with both test scores and being close to NASCAR

# Do we believe this number?

What's a potential issue with just looking at the raw association?

Schools near NASCAR tracks are probably a lot different than schools further away

We want to control for things that are potentially correlated with both test scores and being close to NASCAR

Two broad important things: lead emissions from other sources, socioeconomic status

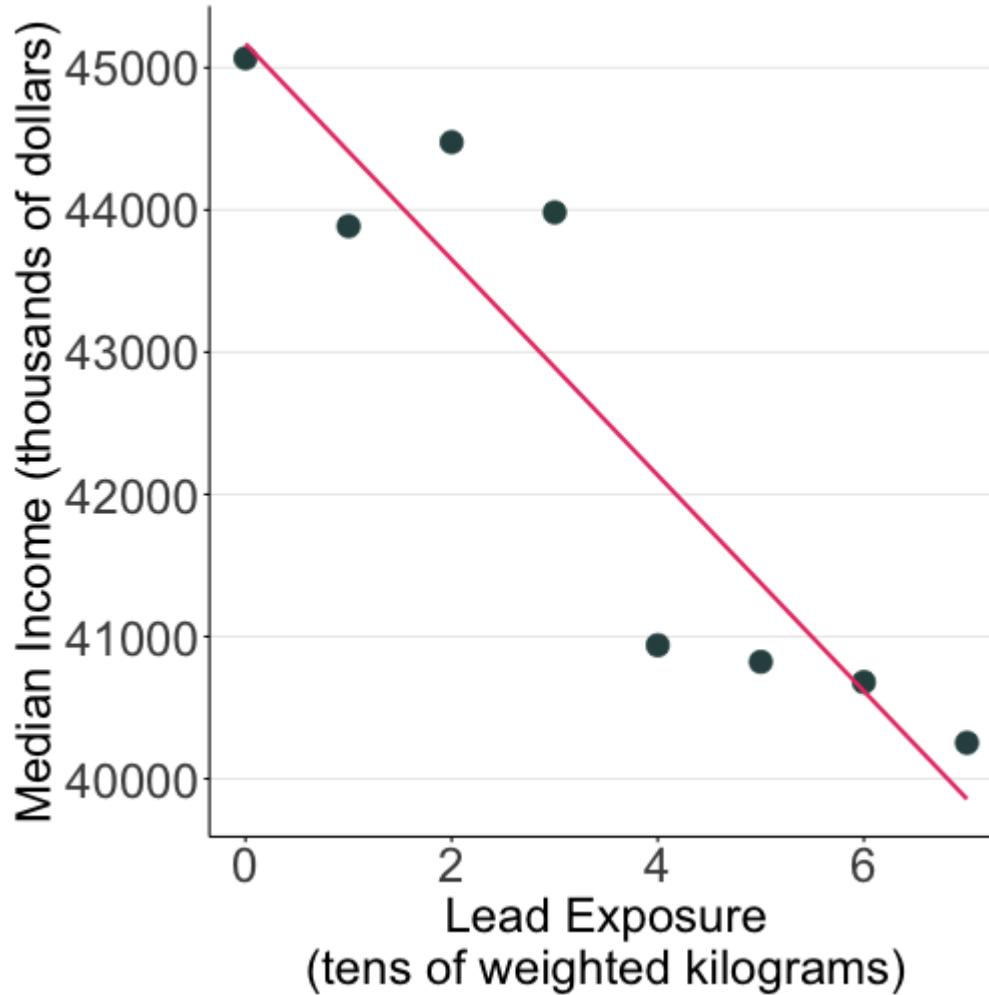
# Do we believe this number?

$$zscore_{sgy} = \beta_0 + \beta_1 nascar\_lead\_weighted_{sgy} + \beta_2 other\_lead_{sgy} + \beta_3 income_{sgy}$$

```
## Estimation results
##   parameter           estimate
## 1 beta_0  (Intercept) -0.846
## 2 beta_1 nascar_lead_weighted -0.0008  (versus -0.004 above)
## 3 beta_2 other_lead          -0.00000006 (other lead = bad!)
## 4 beta_3 income              0.00002 (rich family = good!)
```

Controlling for other things matters: new estimate is 1/4 the size

# Why did this matter?



Mainly because places with  
NASCAR tracks tend to be poorer