



Causality

Identifying causal relationship



Quick Review of Regression

Consider simple linear regression: $Y = a + bX$.

Y is your dependent variable and X is your independent variable.

We want to know how X affects the value of Y .





A Motivating Example

Suppose that you want to answer the following question: “Does eating ice-creams increase a person’s weight?”

To answer this question, which regression should you run? What data should be collected?



A Motivating Example

Suppose that you want to answer the following question: “Does eating ice-creams increase a person’s weight?”


Here, our dependent variable (Y) is a person’s current weight (e.g., $Y = 50$ means the weight is 50 kg).

Our independent variable (X) is the consumption of ice-cream in the previous week (e.g., $X = 4$ means you consumed 4 ice-creams in the least week).



A Motivating Example

We sampled a large number of individuals (say, 1,000 people) and recorded their ice-cream consumption and weight at different time of year, and construct our dataset. Then, we regress Y on X .






A Motivating Example

Surprising, you find that

$$Y = 60 - 4X$$

which suggests that ice-cream consumption *decreases* your weight!

You double and triple checked the data and your regression and cannot find any mistakes. Now, the question is, *what is wrong with our regression?*





A Motivating Example

You are paying high tuitions to receive education. Why are you willing to pay so much money to take courses here?

The reason is that education is an investment. By investing in education, you will be rewarded in the future (e.g., you can make a better salary).

We call this “return to education.”





The Next Problem

A key issue in economics is estimating the return to education.

More specifically, how much more money can you make by taking one extra year's education?

How would you answer this question?



The Simple Idea

One simple idea is to collect data from different individuals. For example, suppose that we collect data from N individuals. For each one, we know his or her income (which we call Y) as well as his or her year of education (which we call X).

Then, we can run the regression $Y = a + bX$.

Here, if you take one extra year education, your income will increase by b . We are done!



The Simple Idea

Then, we can run the regression $Y = a + bX$.

Here, if you take one extra year education, your income will increase by b . We are done!

Any issues here? Discuss it with your classmates!






The Issue

Even for this simple problem, we have a lot of issues...

Gender, Family Background, IQ level, Geographic Location....

We can try to control for these factors in our regression, but there are so many things to control for and we are never sure if we have controlled for everything...




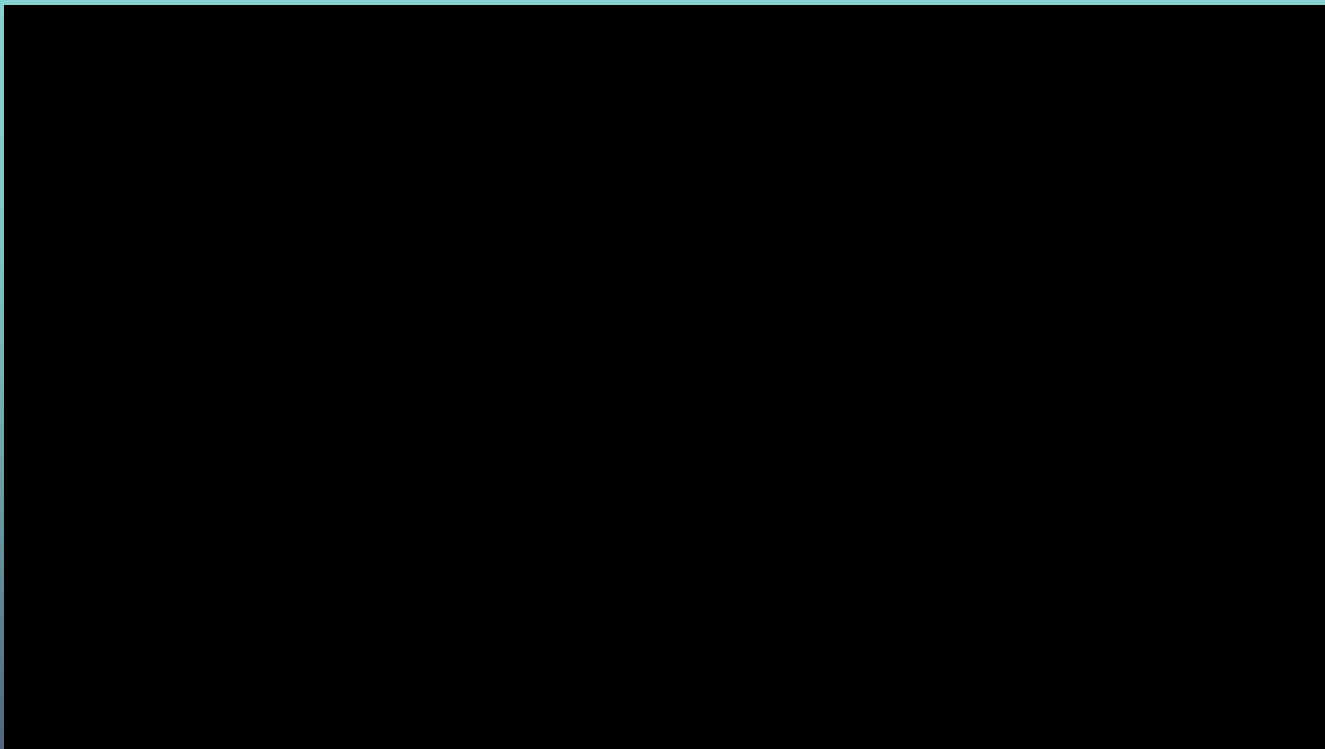


The Issue

We call the variable that you miss the “omitted variable”, and the issue the “omitted variable bias”.

It means that you omit one or more relevant variable in your model specification, and this variable is a determinant of the dependent variable and correlated with one or more of the included independent variables.





Omitted Variable Bias



Exercise I

Suppose that we are regressing Y (the sales of a smartphone) on X (the price of a smartphone) to see how demand changes with price.

What can be an omitted variable in the above regression?





Exercise 2

Suppose that we are regressing Y (life expectancy) on X (the air quality) to see how better air makes people live longer.

What can be an omitted variable in the above regression?



Example

We all know that smoking is bad for health, and quitting smoking is the best thing that a smoker can do.





Example

As data scientists, we want to estimate the effect of quit smoking. For instance, we want to answer the following question: Can a lifetime smoker reduce the chance of developing lung cancer by quitting smoking?

What would you do to answer this question?






Example

The simplest idea: Collect data from a large number of lifetime smokers. Let Y be whether or not a smoker develops lung cancer ($Y = 1$ when developing cancer and $Y = 0$ when no cancer).

Let X denote whether or not the smoker has quit smoking. That is, $X = 1$ if he or she quit smoking and $X = 0$ if he or she did not quit smoking.





Example

Surprisingly, when data scientists first ran this regression, they found out that $b > 0$, that is, quitting smoking *increases* the change of developing lung cancer!

Ironically, this result suggests that we should encourage smokers to continue smoking....





Example

Consider another example. In US, people want to answer the following question: “Does the police reduce the crime rate?”

Here, our dependent variable Y is the crime rate, and our independent variable X is the size of the police force. By running regression, we find that Y increases with X .

We should defund the police!






Example

Consider another example. In US, people want to answer the following question: “Does the police reduce the crime rate?”

The real reason is, when there is more crime, the city tends to hire more police officers. It is Y that causes X , not X causes Y !





Reverse Causality

In many cases X and Y can affect each other.

In other words, X causes Y and Y causes X .

For example, let Y be police force and X be crime rate.

X affects Y : when there is more crime, there will be more police.

Y affects X : when there is more police, there is less crime.





DISCUSSION


Try to find other common examples of reverse causality.





OUR TASK

We want to know how the change of X affects the value of Y . We want to exclude other factors and reserved causality.



A decorative graphic in the top-left corner consisting of a cluster of overlapping hexagons in various shades of teal and light blue, some with white outlines and others solid.

Two Common Causes

A diagram consisting of two large hexagons joined at a single vertical edge. The left hexagon is a dark teal color, and the right hexagon is a lighter teal color. Both hexagons have a thin white border.

Omitted Variable

Reverse Causality



Two Common Solutions



Experiments

Instrumental
Variable

Hypothetical Example

Which of the following schools should you join if you want to make more money in the future?






Hypothetical Example

Which of the following schools can help you make more money in the future?

Suppose that you analyze the data and find that the average salary for the graduates of the three schools are (HKD):

Harvard:	1M
HKU:	500K
Lanxiang (蓝翔):	200K

Can we say that Harvard is the best school that helps you make more money?






Hypothetical Example

We are more interested in the following question:

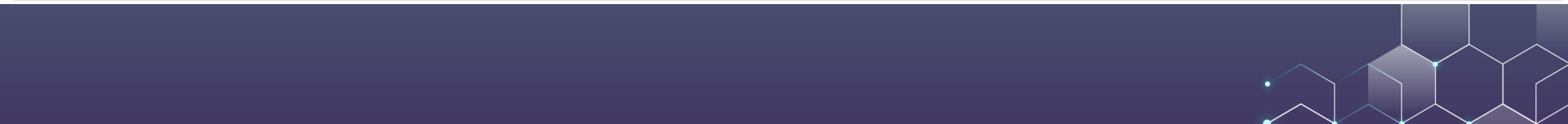
Holding all other things equal (e.g., IQ, family background, education background, gender, ...) would a person make a higher salary if he/she chooses Harvard instead of HKU or Lanxiang?





American Business Schools Sorted by Average Starting Salary and Bonus

School	Average Starting Salary and Bonus	Percent Employed at Graduation	Average GMAT Score (full-time)	Acceptance Rate (full-time)
University of Pennsylvania (Wharton)	\$159,815	82.3%	730	19.2%
Stanford Univeristy	\$159,440	63.9%	737	5.7%
Harvard University	\$158,049	78.9%	731	9.9%
University of Virginia (Darden)	\$153,576	83.4%	713	24.5%
Dartmouth College (Tuck)	\$152,805	80.2%	722	23.0%
Cornell University (Johnson)	\$152,207	80.3%	700	29.9%
Columbia University	\$151,849	69.9%	727	14.0%
University of Chicago (Booth)	\$151,085	88.0%	730	23.5%
University of Michigan, Ann Arbor (Ross)	\$150,052	89.7%	716	25.3%




Hypothetical Example

薪酬指数 排名	学校名称	类型	所在地	是否 985院	是否 211院	薪酬指数	毕业生 平均薪酬
1	清华大学	理工	北京	√	√	88.3	10992
2	上海交通大学	综合	上海	√	√	87.5	10602
3	北京大学	综合	北京	√	√	87.1	10690
4	对外经济贸易大学	财经	北京	0	√	86.4	11032
5	中央财经大学	财经	北京	0	√	86.4	10162
6	北京航空航天大学	理工	北京	√	√	86.2	10179
7	同济大学	理工	上海	√	√	86.1	10473
8	中山大学	综合	广东	√	√	86.1	10048
9	复旦大学	综合	上海	√	√	85.6	10508
10	北京外国语大学	语言	北京	0	√	85.5	10355



Hypothetical Example

Idea:

1. We recruit a large number of high school students.
 2. We **randomly** send the students to the three schools, Harvard, HKU and Lanxiang.
 3. After they graduate, we compare which school's graduates make a higher salary.
- 




Hypothetical Example

Note that now, students are randomly allocated to the three schools. In this case, which school you enter is independent of your personal information: The school you enter has nothing to do with your IQ, your family background, ...

Harvard will get both high IQ and low IQ students. Similarly, Lanxiang will also get both high IQ and low IQ students. Their students' backgrounds are comparable.

Then, if their graduates make different salaries, it is the school that makes the difference and we can rule out all other factors!





One Solution

Of course, this example is more or less impractical...

You cannot force Harvard to admit a student, or force a student to join Lanxiang.

This type of experiment is also illegal...

But the idea is great! We can use it elsewhere.






One Solution

Similarly, we can do this for the smoking problem.

Recall that we want to know if quitting smoking reduces the chance of developing cancer.






One Solution

First, we recruit many smokers to do the experiment.

Second, we randomly assign them into two groups: a control group that continues smoking, and a treatment group.

Individuals in the treatment group are forced to quit smoking.


Later, we examine whether each individual develops cancer in each group.






Pharmaceutical

In the pharmaceutical industry, researchers need to prove that a new drug (X) is effective in curing or alleviating a certain disease (Y). To establish a credible causal relationship, they use “randomized controlled trials (RCTs)”





Pharmaceutical

- We randomly assign participants into two groups, a treatment group and a control group.
 - The treatment group takes the medication ($X=1$) while the control group takes nothing ($X=0$).
 - Finally, we calculate the value of Y (seriousness of disease) for each participant in the study.
- 



Pharmaceutical

However, this alone is *not* enough!

Why? In addition to the medical effect, there may be a placebo effect that comes into play.


When you take the real medication, you feel better, and your mood is good.
However, mood can also affect Y .

We do not really know if the medication works, or patient gets a better mood.





Pharmaceutical

- So, in addition to random trials, we also make the trials “blind”: you do not know which group (i.e., treatment versus control group) that you belong to.
 - In practice, we offer a fake medication (placebo) which resembles the real medication to individuals in the control group. So, everyone gets a pill, and you don’t know whether or not you are getting the real medication.
- 



The background features a teal-to-purple gradient with abstract geometric patterns of hexagons and lines. Some hexagons are solid, while others are outlined. Small teal dots are placed at various points along the lines.

AB Testing

The most commonly used
experimental method




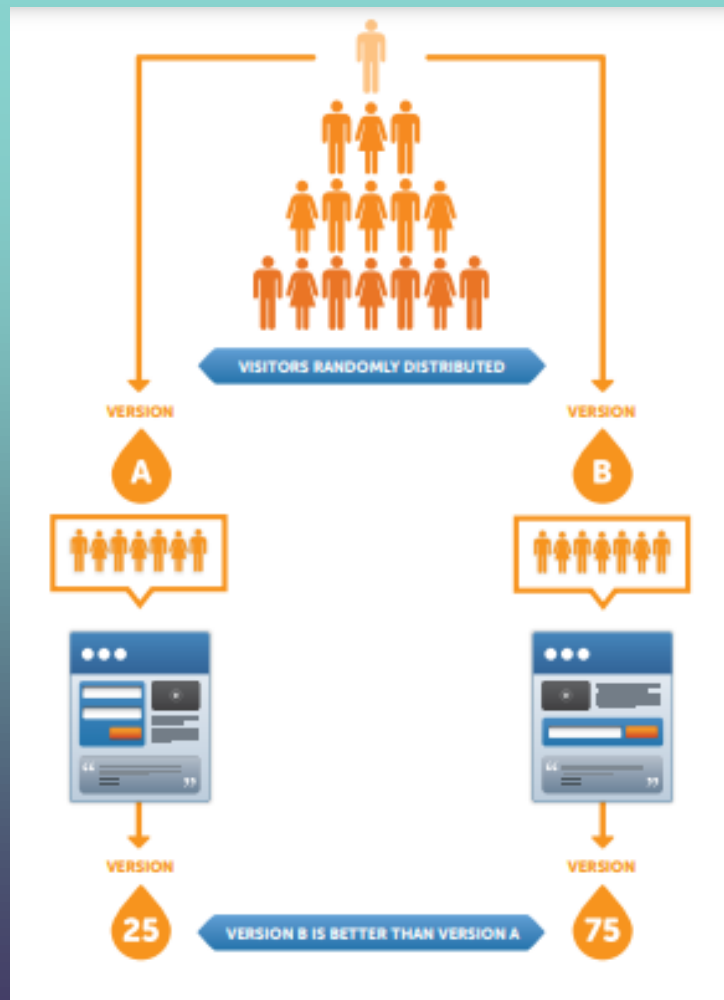
“Whenever we launch a new APP, we run many AB tests in different platforms to find a best name for it. Even though you are 99.9% sure one name is the best, it does not hurt running an AB test.”

---Zhang Yiming, ByteDance CEO
(字节跳动张一鸣)



AB Testing

- AB testing was inspired by RCT used in pharmaceutical industry; it is commonly used in the Internet age.
 - It is commonly used for Website and APPs.
 - Which website design is better?
 - Which APP design is better?
 - Which image is more attractive?
- 






Experiment

Unfortunately, we are not always able to run our experiments or AB testing. For example, experiments can be illegal, too costly, too time consuming, or simply impossible.

For example, suppose that you want to understand how smoking affect one's health; however, you cannot run an AB test forcing some people to smoke/not to smoke. So, how to obtain the results?





Two Common Solutions



Experiments

Instrumental
Variable

Course Overview

2021 Nobel Prize in Economics



Joshua D. Angrist and Guido W. Imbens

“for their methodological contributions to the analysis of causal relationships”



Instrumental Variable

When running an experiment is impossible, we may also consider the instrumental variable approach.

Idea: Find a new variable that affects your X but does not affect your Y directly.



Theory (Optional)

Suppose that you want to estimate how X affects the value of Y . Mathematically, suppose that when X increases by 1, Y will increase by b . We want to find out the value of b .

You find a variable Z that affects X but does not affect Y directly.

People have proved that

$$b = \frac{\text{Cov}(Y,Z)}{\text{Cov}(X,Z)}$$

where cov stands for covariance.



Example

Let us go back to the smoking example.

Here, we want to find out an instrumental variable Z such that (1) when Z changes, people's smoking behavior changes; (2) Z does not affect people's health directly.

Any ideas?





A FACT

Someone may be telling you that he/she is an economist. However, what he/she does everyday is simply looking for instrumental variables.

Scientists that are famous for finding instruments



Daron Acemoglu

Professor, MIT



Joshua Angrist

Professor, MIT



Steve Levitt

Professor,
UChicago



James Snyder

Professor,
Harvard



Discussion

Recall that earlier in this class, we want to understand how education affects one's income. However, we cannot easily run an experiment on this.

So, we may consider finding an instrument. Here, the instrument should (1) affect one's year of education but (2) does not affect one's income directly.

Any ideas?






Discussion

This is really a famous problem! And there is also a famous instrument – the month of birth.

In the US, children have to stay in school until a certain age (e.g., 18 years old). For example, if you are born in Jan 2000, you can leave school in Jan 2018, and so on.






Discussion

However, everyone joins school in September.

Then, two persons born in Jan 2000 and June 2000 join school at the same time but can leave school at different times (Jan 2018 vs. June 2018). So the latter individual takes more education than the former one does.

In this case, your month of birth affects your year of education.



One of the most classic research!

DOES COMPULSORY SCHOOL ATTENDANCE AFFECT SCHOOLING AND EARNINGS?*

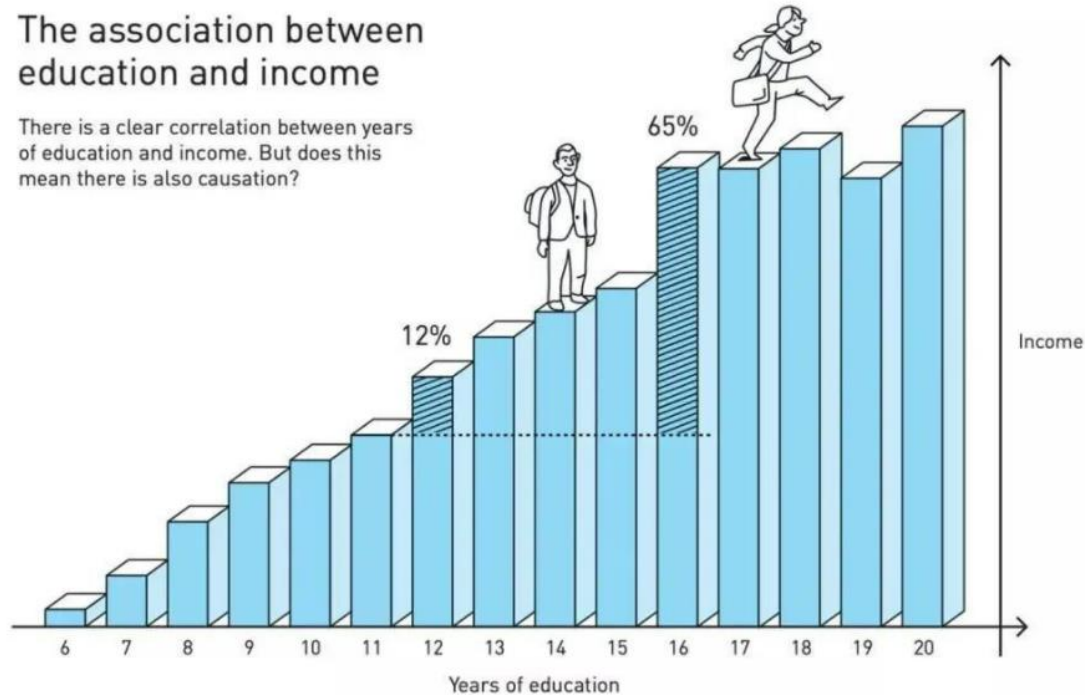
JOSHUA D. ANGRIST AND ALAN B. KRUEGER

We establish that season of birth is related to educational attainment because of school start age policy and compulsory school attendance laws. Individuals born in the beginning of the year start school at an older age, and can therefore drop out after completing less schooling than individuals born near the end of the year. Roughly 25 percent of potential dropouts remain in school because of compulsory schooling laws. We estimate the impact of compulsory schooling on earnings by using quarter of birth as an instrument for education. The instrumental variables estimate of the return to education is close to the ordinary least squares estimate, suggesting that there is little bias in conventional estimates.

One of the most classic research!

The association between education and income

There is a clear correlation between years of education and income. But does this mean there is also causation?



Any Other Instrumental Variable?



THE ELITE ILLUSION: ACHIEVEMENT EFFECTS AT BOSTON AND NEW YORK EXAM SCHOOLS

BY ATILA ABDULKADIOĞLU, JOSHUA ANGRIST, AND PARAG PATHAK¹

Parents gauge school quality in part by the level of student achievement and a school's racial and socioeconomic mix. The importance of school characteristics in the housing market can be seen in the jump in house prices at school district boundaries where peer characteristics change. The question of whether schools with more attractive peers are really better in a value-added sense remains open, however. This paper uses a fuzzy regression-discontinuity design to evaluate the causal effects of peer characteristics. Our design exploits admissions cutoffs at Boston and New York City's heavily over-subscribed exam schools. Successful applicants near admissions cutoffs for the least selective of these schools move from schools with scores near the bottom of the state SAT score distribution to schools with scores near the median. Successful applicants near admissions cutoffs for the most selective of these schools move from above-average schools to schools with students whose scores fall in the extreme upper tail. Exam school students can also expect to study with fewer nonwhite classmates than unsuccessful applicants. Our estimates suggest that the marked changes in peer characteristics at exam school admissions cutoffs have little causal effect on test scores or college quality.



Comment on Machine Learning

Nowadays, machine learning is very powerful in making predictions. That is, given X , machine learning algorithms predict the value of Y .

Many algorithms such as neural networks, naïve Bayesian, matrix factorization etc.

Basically, machine learning algorithms generate a function f such that $Y \approx f(X)$.






Comment on Machine Learning

There is a frequent challenge on machine learning:

“Machine Learning-based projects focus on predicting outcomes rather than understanding causality.”


For this reason, machine learning algorithms are often called “black box” --- we know it works, but we don’t know how it works (只知其然，不知其所以然).





Why should we care about causality?

In an e-commerce context, we could determine which specific factor impacts the decision to purchase a product. With this information, we could better allocate resources to improve a specific KPI. We could also rank the impact of different factors on the purchasing decision. We could determine if a given customer would have purchased a specific product if he/she had not bought other products for the last two years.





Why should we care about causality?

In the agricultural field, we often try to predict if a farmer's crop yield will be lower this year. However, using casual inference, it will become to better understand what steps should we take to increase the harvest.



Scan the QR code to join a test

Code:

