# Lecture 1 09/09/2021

## Chapter 1: Introduction:

### 1.1. Causal Relationship and Ceterus Paribus Analysis

The goal of most empirical studies is to say whether a change in one variable, say $w$, causes a change in another variable, say $y$.

Examples:

Does an increase in years of education causes an increase in monthly salary?

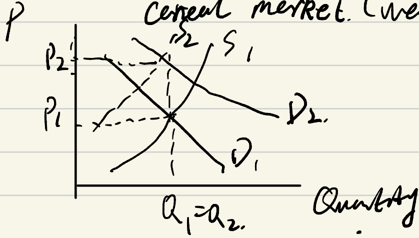
Does mask wearing case a reduction in the probability of testing positive of Covid-19?

Ceterus paribus:

Holding all other (relevant) factors fixed. to uncover a causal relationship between $y$ and $w$ we need to be able to hold other factors fixed.

- Finding that two variables are collerated is rarely enough to conclude that change in one variable cause a change in another.
- this is largely due to the fact that we often deal with non-experimental data.

Cereal market (weekly)




- suppose the price goes up.
- Income in consumers ↑.

CDC study on dinny-out and positive covid-19 test

$$pos_i = \beta_0 + \beta_1 dine_i + u_i$$

$$\beta_1 > 0$$

In general, let y be a variable, we are interested in explaining y using w and a set of other variables (c) as explanatory variables

- In particular, we will focus on the expected response $E(y|w,c)$ which is the expected value of y conditional on w and c.
- We would like to know the effect of w on $E(y|w,c)$
- If w is continuous then we want to know the partial effect of w on $E(y|w,c)$ which is:

$$\frac{d\, E(y|w,c)}{dw}$$

- the list of the controls is completely up to the researcher
- unfortunately, in most cases, elements in c are not always observable.

<u>Exp</u>: y = wage, w = educ, c: (exper, abil)

$$E(wage|w,c) = E(wage|educ, exper, abil)$$

typically innate ability is not observed.

# chapter 2 CE and Related concepts in ECON.

## 2.1 the role of conditional expectations in economics

- In most applied Economics studies the goal is to estimate or test hypothesis about the expectation of one variable
- we refer to the variable as the dependent variable.
- we condition $y$ on a set of explanatory variables usually denoted as $x = (x_1, x_2 \cdots x_n)$
- In many cases, we are interested in evaluating the causal effect of a variable $w$ on the expected value of $y$, holding fixed a vector of controls $c$.
  $\boxed{E(y|w,c)}$ is called the structural conditional expectation
- In many cases, we don't observe one or more variables in $c$.
- Under additional assumption — generally called identification assumptions — we can sometimes recover the structural conditional expectations.

## 2.2. Features of conditional expectation

### 2.2.1 Definitions and Examples

Let $y$ be a random variable, which we will refer to as the explained variable

- Let $x = (x_1, x_2, x_3 \dots x_K)$ be a $1 \times K$ vector of explanatory variables if $E(|y|) < \infty$, then there is a function, say

(2.1) $\mu : \mathbb{R}^K \to \mathbb{R}$ $\quad E(y | x_1, \dots x_K) = \mu(x_1, \dots x_K)$.

or. $E(y|x) = \mu(x)$

$\mu(x)$ determines how the average value of $x$ change

Since $E(y|x)$ is an expectation, it can be obtained from the conditional density $f(y|x)$

- Most of the time the conditional expectation is specified to depend on a finite set of parameters, which gives a parametric model of $E(y|x)$

For $K=2$ explanatory variables, consider the following examples of conditional expectation:

$$E(y|x_1, x_2) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \quad (2.2)$$

$$E(y|x_1, x_2) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_2 x_2^2 \quad (2.3)$$

$$E(y|x_1, x_2) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 \quad (2.4)$$

$$E(y|x_1, x_2) = \exp[\beta_0 + \beta_1 \log(x_1) + \beta_2 x_2] \quad (2.5)$$

## 2.2.2. Partial effect, Elasticity and Semielasticity

- If $y$ and $x$ are related in a deterministic way $y = f(x)$, then we are often interested in how $y$ changes when elements of $x$ change.

Instead we focus on the partial effects of the $x_j$ on the conditional expectation $E(y|x)$

- If $\mu(\cdot)$ is differentiable and $x_1$ is continuous, $\dfrac{d\,\mu(x)}{dx_j}$ allows us to approximate the marginal change in $E(y|x)$ when $x_j$ is increased by a small amount.

For example, 2.2:

$$\frac{dE(y|x)}{dx_1} = \beta_1 \qquad \frac{dE(y|x)}{dx_2} = \beta_2.$$

For Equ 2.4:

$$\frac{dE(y|x)}{dx_1} = \beta_1 + \beta_3 x_2$$

$$\frac{dE(y|x)}{dx_2} = \beta_2 + \beta_2 x_1$$

## 2.2.3 The Error Form models of Conditional Expectation

- when $y$ is a random variable, we would like to explain it in terms of observable variables $x$, it's useful to decompose $y$ as:

Incross. sectn, u is only viewed as unobservable.

$$y = E(y|x) + u \qquad (2.15)$$

$f_u$

u can be any function

$$E(u|x) = 0 \qquad (2.16)$$

-> For convenience.

↳ zero condional mean assumption. (ZCM)

Example:

$$pos_i = E(pos \mid dire) + u_i$$

$u$ = risk preference ($rp$)

For the ZCM to hold we need:

$E(u|dme) = 0 = E(rp|dme) = 0$