

# Introductory Econometrics

## Probability and Statistics Refresher

Monash Econometrics and Business Statistics

Semester 2, 2018

# Outline

- ▶ Reference: Appendices B-1, B-2, B-3, B-4 of the textbook
  - ▶ Random variables (discrete, continuous) and their probability distribution
  - ▶ Mean, variance, standard deviation
  - ▶ Properties of expectation
  - ▶ Covariance and correlation
  - ▶ Joint and conditional distributions
  - ▶ Conditional expectation function as the fundamental target of modelling

# Random variables

- ▶ Economic and financial variables are by nature random. We do not know what their values will be until we observe them.
- ▶ A **random variable** is a rule that assigns a **numerical** outcome to an event in each possible state of the world.
- ▶ For example, the first wage offer that a BCom graduate receives in the job market is a random variable. The value of ASX200 index tomorrow is a random variable. Other examples are ...
- ▶ A **discrete random variable** has a finite number of distinct outcomes. For example, rolling a die is a random variable with 6 distinct outcomes.
- ▶ A **continuous random variable** can take a continuum of values within some interval. For example, rainfall in Melbourne in May can be any number in the range from 0.00 to 200.00 mm.
- ▶ While the outcomes are uncertain, they are not haphazard. The rule assigns each outcome to an event according to a probability.

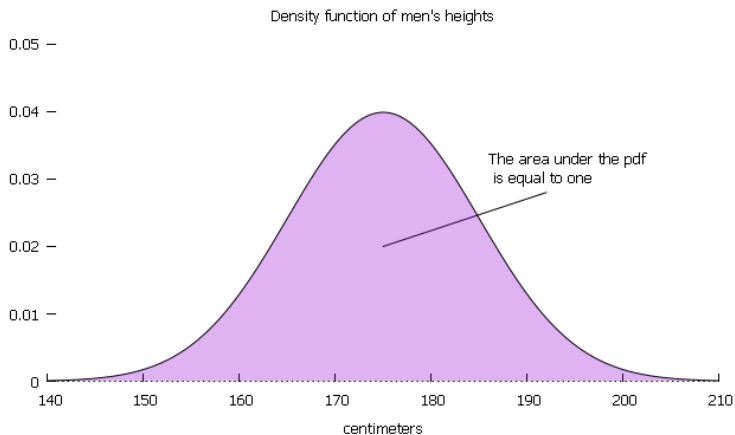
# A random variable and its probability distribution

- ▶ A discrete random variable is fully described by
  - its possible values  $x_1, x_2, \dots, x_m$
  - probability corresponding to each value  $p_1, p_2, \dots, p_m$with the interpretation that  $P(X = x_1) = p_1, P(X = x_2) = p_2, \dots, P(X = x_m) = p_m$ .
- ▶ The **probability density function (pdf)** for a discrete random variable  $X$  is a function  $f$  with  $f(x_i) = p_i, i = 1, 2, \dots, m$  and  $f(x) = 0$  for all other  $x$ .
- ▶ Probabilities of all possible outcomes of a random variable must sum to 1.

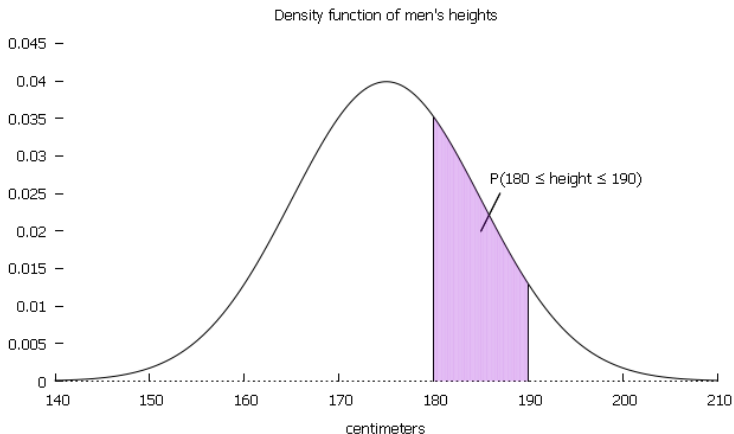
$$\sum_{i=1}^m p_i = p_1 + p_2 + \dots + p_m = 1$$

- ▶ Examples:
  1. Rolling a die
  2. Sex of a baby who is not yet born. Is it a random variable?
  3. The starting wage offer to a BCom graduate
- ▶ The **probability density function (pdf)** for a continuous random variable  $X$  is a function  $f$  such that  $P(a \leq X \leq b)$  is the area under the pdf between  $a$  and  $b$ .
- ▶ The total area under the pdf is equal to 1.

- ▶ Example: Distribution of men's height
- ▶ The area under the pdf is equal to 1



- ▶ The probability of that the height of a randomly selected man lies in a certain interval is the area under the pdf over that interval



# Features of probability distributions: 1. Measures of Central Tendency

Textbook reference B-3

- ▶ **Expected value** or **mean** of a discrete random variable is given by

$$E(X) = p_1x_1 + p_2x_2 + \cdots + p_mx_m = \sum_{i=1}^m p_ix_i$$

and for a continuous random variable is given by

$$E(X) = \int_{-\infty}^{\infty} xf(x)dx$$

- ▶ Intuitively, expected value is the long-run average if we observe  $X$  many, many, many times.
- ▶ It is convention to use the Greek letter  $\mu$  to denote expected value:

$$\mu_X = E(X)$$



- ▶ Another measure of central tendency is the **median** of  $X$ , which is the “middle-most” outcome of  $X$ , i.e.  $x_{med}$  such that  $P(X \leq x_{med}) = 0.5$ . Median is preferred to the mean when the distribution is heavily skewed, e.g. income or house prices.
- ▶ Finally, there is the **mode** which is the most likely value, i.e. the outcome with the highest probability. It is not a widely used measure of central tendency.

## 2. Measures of dispersion

Textbook reference B-3

- ▶ **Variance** of a random variable:

$$\sigma_X^2 = \text{Var}(X) = E(X - \mu_X)^2$$

- ▶ Variance is a measure of spread of the distribution of  $X$  around its mean.
- ▶ If  $X$  is an action with different possible outcomes, then  $\text{Var}(X)$  gives an indication of **riskiness** of that action.
- ▶ **Standard deviation** is the square root of the variance. In finance, standard deviation is called the **volatility** in  $X$ .

$$\sigma_X = \text{sd}(X) = \sqrt{E(X - \mu_X)^2}$$

- ▶ The advantage of standard deviation over variance is that it has the same units as  $X$ .

# Properties of the Expected Value

Textbook reference B-3

1. For any constant  $c$ ,  $E(c) = c$ .
2. For any constants  $a$  and  $b$ ,

$$E(aX + b) = aE(X) + b$$

3. Expected value is a linear operator, meaning that expected value of sum of several variables is the sum of their expected values:

$$E(X + Y + Z) = E(X) + E(Y) + E(Z)$$

- The above three properties imply that for any constants  $a, b, c$  and  $d$  and random variables  $X, Y$  and  $Z$ ,

$$E(a + bX + cY + dZ) = a + bE(X) + cE(Y) + dE(Z)$$

## Question - <http://mars.mu> - Feed Code: Z3DKLD

We have put one quarter of our savings in a term deposit (a risk free investment) with annual return of 2% and invested the other three quarters in an investment fund with expected annual return of 3% and variance of 4.

The expected value of the annual return of our portfolio is

- A.  $\frac{2+3}{2} = 1.5\%$
- B.  $\frac{1}{4} \times 2 + \frac{3}{4} \times 3 = 2.75\%$
- C.  $\frac{3}{4} \times 3 = 2.25\%$
- D.  $\frac{1}{4} \times 2 + \frac{3}{4} \times 3 \times \sqrt{4} = 5\%$
- E.  $\frac{1}{4} \times 0 + \frac{3}{4} \times 4 = 3\%$

- It is important to have in mind that  $E$  is a linear operator, so it “goes through” sums of random variables, but it does not go through non-linear transformations of random variables. For example:

$$E(X^2) \neq (E(X))^2$$

$$E(\log X) \neq \log(E(X))$$

$E(XY) \neq E(X)E(Y)$  unless  $X$  and  $Y$  are statistically independent

- Using properties of expectations, we can now show that  $\text{Var}(X) = E(X^2) - \mu^2$

$$\begin{aligned}\text{Var}(X) &= E(X - \mu)^2 = E(X^2 - 2\mu X + \mu^2) \\ &= E(X^2) - 2\mu E(X) + \mu^2 = E(X^2) - 2\mu^2 + \mu^2 \\ &= E(X^2) - \mu^2\end{aligned}$$

# Properties of the Variance

Textbook reference B-3

1. For any constant  $c$ ,  $\text{Var}(c) = 0$ .
2. For any constants  $a$  and  $b$ ,

$$\text{Var}(aX + b) = a^2 \text{Var}(X)$$

3. There is a third property related to the variance of linear combinations of random variables that is very important and we will see later after we introduce the covariance.

We have put one quarter of our savings in a term deposit (a risk free investment) with annual return of 2% and invested the other three quarters in an investment fund with expected annual return of 3% and variance of 4.

The variance of the annual return of our portfolio is

- A.  $\left(\frac{3}{4}\right)^2 \times 4 = 2.25$
- B.  $\frac{1}{4} \times 0 + \frac{3}{4} \times 4 = 3$
- C.  $\frac{1}{4} \times 2 + \frac{3}{4} \times 4 = 3.25$
- D.  $\left(\frac{1}{4}\right)^2 \times 2 + \left(\frac{3}{4}\right)^2 \times 3 = 1.8125$
- E.  $\left(\frac{1}{4}\right)^2 \times 2 + \left(\frac{3}{4}\right)^2 \times 4 = 2.375$

# Properties of the Conditional Expectation

- ▶ Conditional expectation of  $Y$  given  $X$  is generally a function of  $X$ .
- ▶ Property 1: Conditional on  $X$ , any function of  $X$  is no longer a random variable and can be treated as a known constant, and then the usual properties of expectations apply. For example, if  $X$ ,  $Y$  and  $Z$  are random variables and  $a, b$  and  $c$  are constants, then

$$E(XY \mid X) = XE(Y \mid X)$$

or

$$E((a + bX + cXY + X^2Z) \mid X) = a + bX + cXE(Y \mid X) + X^2E(Z \mid X)$$

- ▶ Property 2: If  $E(Y \mid X) = c$  where  $c$  is a constant that does not depend on  $X$ , then  $E(Y) = c$ . This is intuitive: if no matter what  $X$  happens to be, we always expect  $Y$  to be  $c$ , then the expected value of  $Y$  must be  $c$  regardless of  $X$ , i.e. the unconditional expectation of  $Y$  must be  $c$ .



# Important features of joint probability distribution of two random variables: Measures of Association

Textbook reference B-4

- ▶ Statistical dependence tells us that knowing the outcome of one variable is informative about probability distribution of another.
- ▶ To analyse the nature of dependence, we can look at the **joint probability distribution** of random variables
- ▶ This is too complicated when random variables have many possible outcomes (e.g. per capita income and life span, or returns on Telstra and BHP stocks)
- ▶ We simplify the question to: when  $X$  is above its mean, is  $Y$  more likely to be below or above its mean?
- ▶ This corresponds to the popular notion of  $X$  and  $Y$  being “positively or negatively correlated”

# Covariance

- ▶ Question: “when  $X$  is above its mean, is  $Y$  more likely to be below or above its mean?”
- ▶ We can answer this by looking at the sign of the **covariance between  $X$  and  $Y$**  defined as:

$$\text{Cov}(X, Y) = E((X - \mu_X)(Y - \mu_Y)) = E(XY) - \mu_X\mu_Y$$

- ▶ If  $X$  and  $Y$  are independent  $\text{Cov}(X, Y) = 0$ .
- ▶ For any constants  $a_1, b_1, a_2$  and  $b_2$

$$\text{Cov}(a_1X + b_1, a_2Y + b_2) = a_1a_2\text{Cov}(X, Y)$$

# Correlation

- ▶ Only the sign of covariance is informative. Its magnitude changes when we scale variables.

$$\text{Cov}(aX, bY) = a b \text{Cov}(X, Y)$$

- ▶ A better and unit free measure of association is **correlation** which is defined as:

$$\text{Corr}(X, Y) = \frac{\text{Cov}(X, Y)}{\text{sd}(X)\text{sd}(Y)}$$

- ▶ Correlation is always between -1 and +1, and its magnitude, as well as its sign, is meaningful.
- ▶ Correlation does not change if we change the units of measurement

$$\text{Corr}(a_1X + b_1, a_2Y + b_2) = \text{Corr}(X, Y)$$

# Variance of sums of random variables: Diversification

Textbook reference B4

- ▶ One of the important principles of risk management is “Don’t put all your eggs in one basket.”
- ▶ The scientific basis of this is that:

$$\text{Var}(aX + bY) = a^2 \text{Var}(X) + b^2 \text{Var}(Y) + 2ab \text{Cov}(X, Y)$$

- ▶ Example: You have the choice of buying shares of company A with mean return of 10 percent and standard deviation of 5 percent, or shares of company B with mean return of 10 percent and standard deviation of 10 percent. Which would you prefer?
- ▶ Obviously A is less risky, and you prefer A to B.

## Variance of sums of random variables: Diversification

- ▶ Now consider a portfolio of investing 0.8 of your capital in company A and the rest in B, where, as before, A has mean return of 10 percent and standard deviation of 5 percent, and B has mean return of 10 percent and standard deviation of 10 percent. What are the return and the risk of this position with the added assumption that the returns to A and B are independent.
- ▶ Denoting the portfolio return by  $Z$ , we have

$$Z = 0.8A + 0.2B$$

$$E(Z) = E(0.8A + 0.2B) =$$

$$\text{Var}(Z) = \text{Var}(0.8A + 0.2B) =$$

- ▶ We can see that this portfolio has the same expected return as A, and is safer than A.

## Diversification in econometrics - Averaging

- ▶ Suppose we are interested in starting salaries of BCom graduates. This is a random variable with many possibilities and a probability distribution.
- ▶ Let's denote this random variable by  $Y$ . We also denote its population mean and variance by  $\mu$  and  $\sigma^2$ . We are interested in estimating  $\mu$ , which is the expected wage of a BCom graduate.
- ▶ Suppose we choose one BCom graduate at random and denote his/her starting salary by  $Y_1$ . Certainly  $Y_1$  is also a random variable with the same possible outcomes and probabilities as  $Y$ . Therefore  $E(Y_1) = \mu$ . So it is OK to take the value of  $Y_1$  as an estimate of  $\mu$ , and the variance of this estimator is  $\sigma^2$ .
- ▶ But if we take 2 independent observations and use their average as our estimator of  $\mu$ , we have:

$$\begin{aligned}E\left(\frac{1}{2}(Y_1 + Y_2)\right) &= \frac{1}{2}(\mu + \mu) = \mu \\ \text{Var}\left(\frac{1}{2}(Y_1 + Y_2)\right) &= \frac{1}{4}\text{Var}(Y_1) + \frac{1}{4}\text{Var}(Y_2) \\ &= \frac{1}{4}(\sigma^2 + \sigma^2) = \sigma^2/2\end{aligned}$$

## Diversification in econometrics - Averaging

- ▶ Now consider a sample of  $n$  independent observations of starting salaries of BCom graduate  $\{Y_1, Y_2, \dots, Y_n\}$
- ▶  $Y_1$  to  $Y_n$  are *i.i.d.* (independent and identically distributed) with mean  $\mu$  and variance  $\sigma^2$ .
- ▶ Their average is a portfolio of that gives each of these  $n$  random variables the same weight of  $\frac{1}{n}$ . So

$$E(\bar{Y}) = E\left(\frac{1}{n} \sum_{i=1}^n Y_i\right) = \frac{1}{n} \sum_{i=1}^n E(Y_i) = \frac{1}{n} \sum_{i=1}^n \mu = \mu.$$

$$\begin{aligned} \text{Var}(\bar{Y}) &= \text{Var}\left[\frac{1}{n} \sum_{i=1}^n Y_i\right] = \frac{1}{n^2} \text{Var}\left[\sum_{i=1}^n Y_i\right] \\ &= \frac{1}{n^2} \sum_{i=1}^n \text{Var}(Y_i) = \frac{1}{n^2} \sum_{i=1}^n \sigma^2 = \frac{\sigma^2}{n}. \end{aligned}$$

- ▶ The sample average has the same expected value as  $Y$  but a lot less risk. In this way, we use the scientific concept of diversification in econometrics to find better estimators!

# Key concepts and their importance

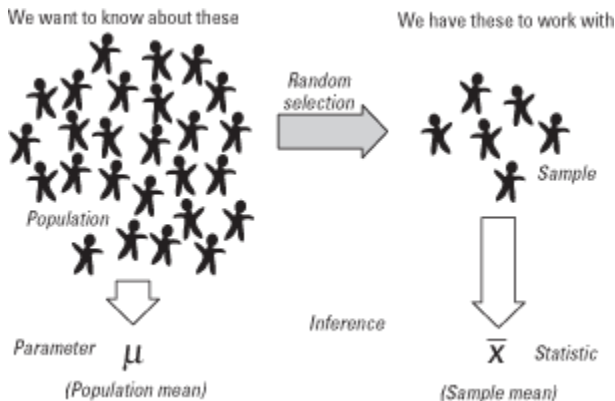
- ▶ Business and economic variables can be thought of as **random variables** whose outcomes are determined by their **probability distribution**.
  - ▶ A measure of central tendency of the distribution of a random variable is its **expected value**.
  - ▶ Important measures of dispersion of a random variable are **variance** and **standard deviation**. These are used as measures of risk.
- ▶ **Covariance** and **correlation** are measures of linear statistical dependence between two random variables.
  - ▶ Correlation is unit free and measures the strength and direction of association.
  - ▶ Statistical dependence or association does not imply causality.
  - ▶ Two random variables that have non-zero covariance or correlation are statistically dependent, meaning that knowing the outcome of one of the two random variables gives us useful information about the other.
  - ▶ **Averaging** is a form of **diversification** and it reduces risk.



## **Let's Play**

[http://www.onlinestatbook.com/stat\\_sim/sampling\\_dist/](http://www.onlinestatbook.com/stat_sim/sampling_dist/)

# Modelling mean



$$E(y | x) = \beta_0 + \beta_1 x$$

(Conditional expectation function)

$$\hat{y} = \widehat{E(y | x)} = \hat{\beta}_0 + \hat{\beta}_1 x$$

(Sample regression function)

# Laws of Probability

- ▶ To understand what a conditional expectation is, we start with laws of probability
1. Probability of any event is a number between 0 and 1. The probabilities of all possible outcomes of a random variable add up to 1
  2. If  $A$  and  $B$  are mutually exclusive events then

$$P(A \text{ or } B) = P(A) + P(B)$$

Example: You role a fair die. What is the probability of the die showing a number less than or equal to 2?

3. If  $A$  and  $B$  are two events, then

$$P(A | B) = \frac{P(A \text{ and } B)}{P(B)}$$

Example: You role a fair die. What is the probability that it shows 1 given that it is showing a number less than or equal to 2?

# Joint probability density function

- ▶ The ultimate goal of this unit is to study the relationship between one variable  $y$  with many variables  $x_1$  to  $x_k$ . But let's start with only one  $x$ , and with the discrete case.
- ▶ Suppose  $y$  is the number of bathrooms and  $x$  is the number of bedrooms in an apartment in Melbourne. Assume  $y$  has two possible values, 1 and 2, and  $x$  has three possible values 1, 2 and 3. The joint pdf gives us the probabilities of every possible outcome of  $(x, y)$ .

$y \downarrow, x \rightarrow$	1	2	3	marginal $f_y$
1	0.40	0.24	0.04	
2	0.00	0.16	0.16	
marginal $f_x$				

- ▶ The entries show the probabilities of different possible combination of bedrooms and bathrooms  $(x, y)$ . For example the top left cell shows  $P(x = 1 \& y = 1) = 0.40$ .
- ▶ Check the first law of probability: all probabilities are between 0 and 1 and the probabilities of all possible outcomes sum to 1
- ▶ Using the second law of probability, we can use the joint pdf to deduce the pdf of  $x$  by itself (called the marginal density of  $x$ ), and also the marginal density of  $y$

## Conditional density

- ▶ Using the third law of probability, we can also deduce the conditional distribution of number of bathrooms in an apartment given that it has 1 bedroom.

$$P(y = 1 \mid x = 1) = \frac{P(y = 1 \ \& \ x = 1)}{P(x = 1)} = \frac{0.40}{0.40} = 1.00$$

$$P(y = 2 \mid x = 1) =$$

- ▶ Similarly, we can deduce the conditional distribution of  $y$  given  $x = 2$

$$P(y = 1 \mid x = 2) = \frac{P(y = 1 \ \& \ x = 2)}{P(x = 2)} =$$

$$P(y = 2 \mid x = 2) =$$

- ▶ And  $y$  given  $x = 3$

$$P(y = 1 \mid x = 3) =$$

$$P(y = 2 \mid x = 3) =$$

## Conditional expectation function

- Each of these conditional densities has an expected value

$$\begin{array}{cc} y \mid x = 1 & f_{y|x=1} \\ 1 & 1.00 \\ 2 & 0.00 \end{array} \Rightarrow E(y \mid x = 1) = 1 \times 1.00 + 2 \times 0.00 = 1.00$$

$$\begin{array}{cc} y \mid x = 2 & f_{y|x=2} \\ 1 & 0.60 \\ 2 & 0.40 \end{array} \Rightarrow E(y \mid x = 2) = 1 \times 0.60 + 2 \times 0.40 = 1.40$$

$$\begin{array}{cc} y \mid x = 3 & f_{y|x=3} \\ 1 & 0.20 \\ 2 & 0.80 \end{array} \Rightarrow E(y \mid x = 3) = 1 \times 0.20 + 2 \times 0.80 = 1.80$$

- Plot the expected values for different values of  $x$ . Do they fit on a straight line? What is the equation of that line?

- ▶ When  $y$  and  $x$  have many possible outcomes or when they are continuous random variables (like birth weight and number of cigarettes during pregnancy, or price of a house and its land size) we cannot enumerate the joint density and perform the same exercise
- ▶ Therefore we go after the conditional expectation function directly

$$E(y \mid x) = \beta_0 + \beta_1 x \quad (\text{PRF})$$

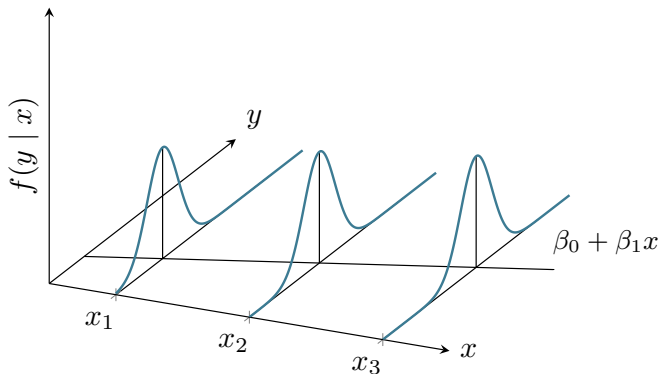
- ▶ For example, if  $y$  is the price of a house and  $x$  is its area, the mean of the price of houses with area  $x$  is given by  $\beta_0 + \beta_1 x$
- ▶ The price of each house can be written as random variations around this central value

$$y = \beta_0 + \beta_1 x + u$$

where  $u$  is a random variable with  $E(u \mid x) = 0$ , which implies that  $E(u) = 0$  also



# The simple linear regression model in a picture



# The simple linear regression model in equation form

- ▶ The following equation specifies the conditional mean of  $y$  given  $x$

$$y = \beta_0 + \beta_1 x + u \text{ with } E(u | x) = 0$$

- ▶ It is an incomplete model because it does not specify the probability distribution of  $y$  conditional of  $x$
- ▶ If we add the assumptions that  $Var(u | x) = \sigma^2$  and that the conditional distribution of  $u$  given  $x$  is normal, then we have a complete model, which is called the “classical linear model” and was shown in the picture on the previous slide.
- ▶ In summary: we make the assumption that in the big scheme of things, data are generated by this model, and we want to use observed data to learn the unknowns  $\beta_0$ ,  $\beta_1$  and  $\sigma^2$  in order to predict  $y$  using  $x$ .

# Summary

- ▶ We reviewed some fundamentals of probability:
  - ▶ Random variables (discrete, continuous) and their probability distribution
  - ▶ Mean, variance, standard deviation
  - ▶ Expectation, covariance and correlation
  - ▶ Joint and conditional probability distributions
- ▶ We established that the problem of finding good estimators and the problem of forming optimal portfolios are based on the same principles.
- ▶ We concluded by establishing that the conditional expectation function of  $y$  given  $x$  as the vehicle for predicting  $y$  using  $x$ .
- ▶ Next week we learn how to estimate the parameters of the conditional expectation function.