# PRINCIPLES OF ECONOMETRICS $\underline{5^{TH} EDITION}$

# ANSWERS TO ODD-NUMBERED EXERCISES IN APPENDIX B

(a) 
$$E(\bar{X}) = E\left[\frac{1}{n}(X_1 + X_2 + ... + X_n)\right] = \frac{1}{n}(E(X_1) + E(X_2) + ... + E(X_n))$$

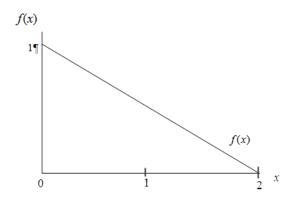
$$= \frac{1}{n}(\mu + \mu + ... + \mu) = \frac{n\mu}{n} = \mu$$

(b) 
$$\operatorname{var}\left(\overline{X}\right) = \operatorname{var}\left(\frac{1}{n}\left(X_1 + X_2 + \dots + X_n\right)\right)$$
$$= \frac{1}{n^2}\left(\operatorname{var}\left(X_1\right) + \operatorname{var}\left(X_2\right) + \dots + \operatorname{var}\left(X_n\right)\right)$$
$$= \frac{1}{n^2}n\,\sigma^2 = \frac{\sigma^2}{n}$$

Since  $X_1, X_2, ..., X_n$  are independent random variables, their covariances are zero. This result was used in the second line of the equation which would contain terms like  $cov(X_i, X_i)$  if these terms were not zero.

# **EXERCISE B.3**

(a) The probability density function is shown below.



- (b) Total area of the triangle is half the base multiplied by the height; i.e., the area is  $0.5 \times 2 \times 1 = 1$
- (c) When x = 1,  $f(x) = f(1) = \frac{1}{2}$ .

Using geometry,  $P(X \ge 1)$  is given by the area to the right of 1 which is  $P(X \ge 1) = \frac{1}{2} \times 1 \times \frac{1}{2} = \frac{1}{4}$ .

Using integration,

$$P(X \ge 1) = \int_{1}^{2} \left( -\frac{1}{2}x + 1 \right) dx = \left( -\frac{1}{4}x^{2} + x \right) \Big|_{1}^{2} = (-1 + 2) - \left( -\frac{1}{4} + 1 \right) = \frac{1}{4}$$

(d) When  $x = \frac{1}{2}$ ,  $f(\frac{1}{2}) = \frac{3}{4}$ 

Using geometry,

$$P(X \le \frac{1}{2}) = 1 - P(X > \frac{1}{2}) = 1 - \frac{1}{2} \times 1\frac{1}{2} \times \frac{3}{4} = \frac{7}{16}$$

Using integration,

$$P\left(X \le \frac{1}{2}\right) = \int_0^{1/2} \left(-\frac{1}{2}x + 1\right) dx = \left(-\frac{1}{4}x^2 + x\right)\Big|_0^{1/2} = -\frac{1}{16} + \frac{1}{2} = \frac{7}{16}$$

(e) For a continuous random variable the probability of observing a single point is zero.

Thus, 
$$P(X = 1\frac{1}{2}) = 0$$
.

(f) The mean is given by

$$E(X) = \int_0^2 x f(x) dx = \int_0^2 \left( -\frac{1}{2} x^2 + x \right) dx = \left( -\frac{1}{6} x^3 + \frac{1}{2} x^2 \right) \Big|_0^2 = \left( -\frac{8}{6} + \frac{4}{2} \right) = \frac{2}{3}$$

The second moment is given by

$$E(X^{2}) = \int_{0}^{2} x^{2} f(x) dx = \int_{0}^{2} \left( -\frac{1}{2} x^{3} + x^{2} \right) dx = \left( -\frac{1}{8} x^{4} + \frac{1}{3} x^{3} \right) \Big|_{0}^{2} = \left( -\frac{16}{8} + \frac{8}{3} \right) = \frac{2}{3}$$

The variance is given by

$$var(X) = E(X^2) - [E(X)]^2 = \frac{2}{3} - \left(\frac{2}{3}\right)^2 = \frac{2}{9}$$

(g) The cumulative distribution function is given by

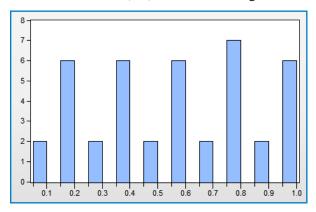
$$F(x) = \int_0^x f(t)dt = \int_0^x \left(-\frac{1}{2}t + 1\right)dt = \left(-\frac{1}{4}t^2 + t\right)\Big|_0^x = x\left(-\frac{x}{4} + 1\right)$$

#### **EXERCISE B.5**

After setting up a workfile for 41 observations, the following EViews program can be used to generate the random numbers

series x
x(1)=79
scalar m=100
scalar a=263
scalar cee=71
for !i= 2 to 41
scalar q=a\*x(!i-1)+cee
x(!i)=q-m\*@ceiling(q/m)+m
next
series u=x/m

If the random number generator has worked well, the observations in U should be independent draws of a uniform random variable on the (0,1) interval. A histogram of these numbers follows:



These numbers are far from random. There are no observations in the intervals (0.10,0.15), (0.20,0.25), (0.30,0.35), ... Moreover, the frequency of observations in the intervals (0.05,0.10), (0.25,0.30), (0.45,0.50), ... is much less than it is in the intervals (0.15,0.20), (0.35,0.40), (0.55,0.60), ... The random number generator is clearly not a good one.

# **EXERCISE B.7**

Let  $E_{X,Y}$  be an expectation taken with respect to the joint density for (X,Y);  $E_X$  and  $E_Y$  are expectations taken with respect to the marginal distributions of X and Y, and  $E_{Y|X}$  is an expectation taken with respect to the conditional distribution of Y given X.

Now, 
$$\operatorname{cov}(Y, g(X)) = 0$$
 if  $E_{X,Y}(Y \times g(X)) = E_{X,Y}(Y) \times E_{X,Y}(g(X))$ .

Using iterated expectations, we can write

$$\begin{split} E_{X,Y} \big( Y \times g(X) \big) &= E_X \left[ E_{Y|X} \left( Y \times g(X) \right) \right] \\ &= E_X \left[ g(X) E_{Y|X} \left( Y \right) \right] \\ &= E_X \left[ g(X) \right] \times E_Y \left( Y \right) \\ &= E_{X,Y} \left[ g(X) \right] \times E_{X,Y} \left( Y \right) \end{split}$$

#### **EXERCISE B.9**

The cumulative distribution function for *X* is given by  $F(x) = \int_{0}^{x} \left(\frac{3t^2}{8}\right) dt = \frac{t^3}{8} \Big|_{0}^{x} = \frac{x^3}{8}$ .

(a) 
$$P(0 < X < \frac{1}{2}) = F(\frac{1}{2}) = \frac{1}{64}$$

(b) 
$$P(1 < X < 2) = F(2) - F(1) = \frac{7}{8}$$

After setting up a workfile for 41 observations, the following EViews program can be used to generate the random numbers U1.

```
series x
x(1)=1234567
scalar m=2^32
scalar a=1103515245
scalar cee=12345
for !i= 2 to 1001
scalar q=a*x(!i-1)+cee
x(!i)=q-m*@ceiling(q/m)+m
next
series u1=x/m
```

If the random number generator has worked well, the observations on U1 should be independent draws of a uniform random variable on the (0,1) interval. Histograms of these numbers and those from U2 obtained using the seed value x(1)=95992 follow:

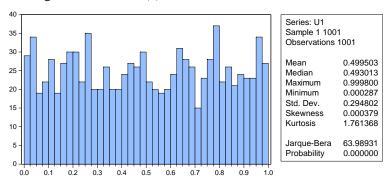


Figure xr-b.11(a) Histogram and summary statistics for *U1* 

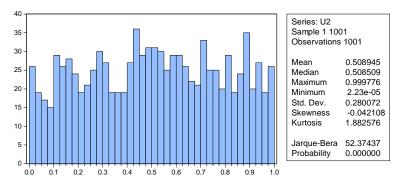


Figure xr-b.11(b) Histogram and summary statistics for U2

The histograms are approximately uniformly distributed, implying the random number generator is a good one. The sample means, standard deviations and correlation are

*U1*: 
$$\overline{X} = 0.4995$$
  $s = 0.2948$   $cor(U1, U2) = 0.0471$ 
*U2*:  $\overline{X} = 0.5089$   $s = 0.2801$ 

These sample quantities are very close to the population values  $\mu = 0.5$ ,  $\sigma = 0.2887$  and  $\rho = 0$ .

(a) The volume under the joint pdf is

$$\int_{0}^{2} \int_{0}^{y} \left(\frac{1}{2}\right) dx \, dy = \int_{0}^{2} \left[\frac{x}{2}\Big|_{0}^{y}\right] dy = \int_{0}^{2} \left(\frac{y}{2}\right) dy = \frac{y^{2}}{4}\Big|_{0}^{2} = 1$$

(b) The marginal *pdf* for *X* is  $f(x) = 1 - \frac{x}{2}$ .

The marginal pdf for Y is  $f(y) = \frac{y}{2}$ .

- $(c) P\left(X < \frac{1}{2}\right) = \frac{7}{16}$
- (d) The *cdf* for Y is  $F(y) = \frac{y^2}{4}$ .
- (e) The conditional pdf f(x|y) is given by

$$f(x|y) = \frac{f(x,y)}{f(y)} = \frac{1/2}{y/2} = \frac{1}{y}$$
 implying  $f(x|Y) = \frac{3}{2} = \frac{2}{3}$ 

The required probability is  $P\left(X < \frac{1}{2} | Y = \frac{3}{2}\right) = \frac{1}{3}$ .

X and Y are not independent because  $P\left(X < \frac{1}{2} \mid Y = \frac{3}{2}\right) \neq P\left(X < \frac{1}{2}\right)$ .

(f) The mean of Y is  $E(Y) = \frac{4}{3}$ .

The second moment of Y is  $E(Y^2) = 2$ .

The variance of Y is  $var(Y) = \frac{2}{9}$ .

(g) From part (e),

$$E(X \mid Y) = \int_0^y x f(x \mid y) dx = \int_0^y \left(\frac{x}{y}\right) dx = \frac{x^2}{2y} \Big|_0^y = \frac{y}{2}$$

$$E(X) = E_Y \left[ E(X \mid Y) \right] = \int_0^2 \left( \frac{y}{2} \right) f(y) dy = \int_0^2 \left( \frac{y^2}{4} \right) dy = \frac{y^3}{12} \Big|_0^2 = \frac{2}{3}$$

We can check this result by using the marginal pdf for X to find E(X):

$$E(X) = \int_0^2 x f(x) dx = \int_0^2 \left( x - \frac{x^2}{2} \right) dx = \left( \frac{x^2}{2} - \frac{x^3}{6} \right) \Big|_0^2 = 2 - \frac{4}{3} = \frac{2}{3}$$

(a) 
$$\operatorname{var}(X) = E(X^2) - [E(X)]^2 = 8.9 - 2.7^2 = 1.61$$

(b) 
$$\operatorname{var}(X \mid Y = 2) = E(X^2 \mid Y = 2) - [E(X \mid Y = 2)]^2 = 9.3 - 2.7^2 = 2.01$$
  
 $\operatorname{var}(X \mid Y = 3) = E(X^2 \mid Y = 3) - [E(X \mid Y = 3)]^2 = 8.9 - 2.7^2 = 1.61$ 

These two conditional variances are not equal.

(c) 
$$E(X | Y = 1) = E(X | Y = 2) = E(X | Y = 3) = 2.7$$
.

$$E(X) = \sum_{i=1}^{3} E(X \mid Y = i) P(Y = i) = 2.7 \times 0.2 + 2.7 \times 0.5 + 2.7 \times 0.3 = 2.7$$

(d) 
$$E(XY) = \sum_{x=1}^{4} \sum_{y=1}^{3} xyf(x, y) = 5.67$$

(e) 
$$\operatorname{cov}(X,Y) = E(XY) - E(X)E(Y) = 5.67 - 2.7 \times 2.1 = 0$$

This is an example of random variables whose covariance is zero despite the fact that they are not independent.

(f) The correlation between *X* and *Y* is 
$$corr(X,Y) = \frac{cov(X,Y)}{\sqrt{var(X)var(Y)}} = 0$$

#### **EXERCISE B.17**

(a) The values that *X* can take and their probabilities of occurring, where *X* is the number of heads occurring in two flips of a fair coin, are given in the first two columns of the following table.

x	f(x)	F(x)
0	1/4	1/4
1	$\frac{1}{2}$	3/4
2	1/4	1

$$P(X \le 1.5) = P(X = 0) + P(X = 1) = \frac{1}{4} + \frac{1}{2} = \frac{3}{4}$$

(b) The values of the cumulative distribution function of X are given in the third column of the table in part (a).

$$P(X \le 1.5) = F(1.5) = F(1) = \frac{3}{4}$$

(c) The pdf for W = 2X is given in the following table.

w	f(w)
0	1/4
2	$\frac{1}{2}$
4	1/4

(d) Expected winnings are given by

$$E(W) = 0 \times \frac{1}{4} + 2 \times \frac{1}{2} + 4 \times \frac{1}{4} = 2$$

(e) Let Y = 1 if the first flip is a head and Y = 0 if the first flip is a tail. Then,

$$P(X = 0 | Y = 1) = 0$$

$$P(X = 1 | Y = 1) = \frac{1}{2}$$

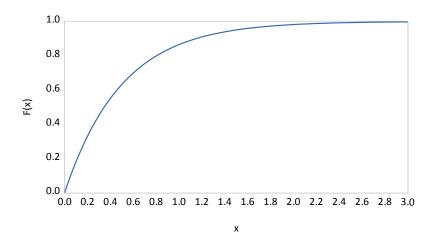
$$P(X = 2 | Y = 1) = \frac{1}{2}$$

(f) The conditional expectation of W = 2X given that the first flip is a head is

$$E(W \mid Y = 1) = 2 \times \frac{1}{2} + 4 \times \frac{1}{2} = 3$$

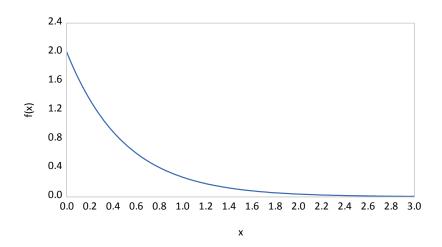
# **EXERCISE B.19**

(a) A graph of the *cdf* follows

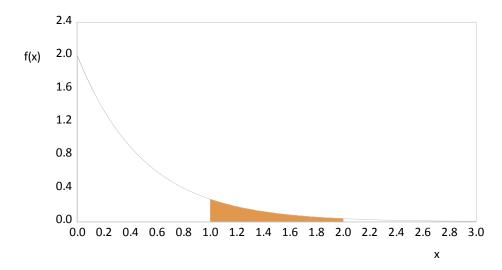


(b) P(1 < X < 2) = F(2) - F(1) = 0.1353 - 0.0183 = 0.1170

(c) 
$$f(x) = \frac{dF(x)}{dx} = \frac{d(1 - e^{-2x})}{dx} = 2e^{-2x}$$



(d) P(1 < X < 2) is given by the shaded area in the following graph.



# **EXERCISE B.21**

The marginal pdf's for Y and X are

у	f(y)	-	x	f(x)
1	0.2	·-	1	0.3
2	0.5		2	0.1
3	0.3		3	0.2

- (a) var(Y) = 0.49
- (b) The conditional distributions for Y for each possible value of X are given in the following table.

у	$f(y \mid X = 1)$	$f(y \mid X = 2)$	$f(y \mid X = 3)$	$f(y \mid X = 4)$
1	$\frac{0.01}{0.3} = 0.0333$	$\frac{0.07}{0.1} = 0.7$	$\frac{0.09}{0.2} = 0.45$	$\frac{0.03}{0.4} = 0.075$
2	$\frac{0.2}{0.3} = 0.6667$	$\frac{0}{0.1} = 0$	$\frac{0.05}{0.2} = 0.25$	$\frac{0.25}{0.4} = 0.625$
3	$\frac{0.09}{0.3} = 0.3$	$\frac{0.03}{0.1} = 0.3$	$\frac{0.06}{0.2} = 0.3$	$\frac{0.12}{0.4} = 0.3$

$$E(Y \mid X = 1) = 2.26667$$
  $E(Y \mid X = 2) = 1.6$   $E(Y \mid X = 3) = 1.85$   $E(Y \mid X = 4) = 2.225$ 

(c) We have,

$$\sum_{x=1}^{4} \left[ E(Y \mid X = x) - E(Y) \right]^{2} f(x) = (2.26667 - 2.1)^{2} \times 0.3 + (1.6 - 2.1)^{2} \times 0.1 + (1.85 - 2.1)^{2} \times 0.2 + (2.225 - 2.1)^{2} \times 0.4$$

$$= 0.0521$$

This represents the first term in (B.27). It is the variance of the conditional mean.

(d) 
$$\operatorname{var}(Y \mid X = 1) = E(Y^2 \mid X = 1) - [E(Y \mid X = 1)]^2 = 5.4 - 2.26667^2 = 0.2622$$

$$\operatorname{var}(Y \mid X = 2) = E(Y^2 \mid X = 2) - [E(Y \mid X = 2)]^2 = 3.4 - 1.6^2 = 0.84$$

$$\operatorname{var}(Y \mid X = 3) = E(Y^2 \mid X = 3) - [E(Y \mid X = 3)]^2 = 4.15 - 1.85^2 = 0.7275$$

$$\operatorname{var}(Y \mid X = 4) = E(Y^2 \mid X = 4) - [E(Y \mid X = 4)]^2 = 5.275 - 2.225^2 = 0.3244$$

(e) 
$$\sum_{x=1}^{4} \left[ var(Y \mid X = x) \right] f(x) = 0.2622 \times 0.3 + 0.84 \times 0.1 + 0.7275 \times 0.2 + 0.3244 \times 0.4 = 0.4379$$

This represents the second term in (B.27). It is the mean of the conditional variances.

(f) We have,

$$var(Y) = \sum_{x=1}^{4} \left[ E(Y \mid X = x) - E(Y) \right]^{2} f(x) + \sum_{x=1}^{4} \left[ var(Y \mid X = x) \right] f(x)$$
$$= 0.0521 + 0.4379 = 0.49$$

This result agrees with that from part (a).

#### **EXERCISE B.23**

(a) 
$$P(X = 2 | \mu = 2) = 0.27067$$

(b) 
$$P(X \ge 2) = 1 - P(X = 0) - P(X = 1) = 0.59399$$

(c) 
$$P(X \ge 2 \mid X \ge 1) = \frac{P[(X \ge 2) \cap (X \ge 1)]}{P(X \ge 1)} = \frac{0.59399}{1 - 0.13534} = 0.68696$$

(a) Chebyshev's inequality is  $P(|X - \mu| \ge \varepsilon) \le \sigma^2/\varepsilon^2$ . When  $\varepsilon = k\sigma$ , it becomes

$$P(|X-\mu| \ge k\sigma) \le \frac{1}{k^2}$$

(b) If k = 2,  $\mu = 1$  and  $\sigma^2 = 1$ , then Chebyshev's inequality becomes  $P(|X - 1| \ge 2) \le 0.25$ . For a normal distribution where  $X \sim N(1,1)$  and  $Z = (X - 1) \sim N(0,1)$ ,

$$P(|X-1| \ge 2) = 2 \times (1 - P(Z \le 2)) = 2 \times (1 - 0.9772) = 0.0456$$

Since 0.0456 < 0.25, this result is in line with Chebyshev's inequality.

(c) If U is a uniform random variable on the interval [0, 1], then  $\mu = E(U) = 0.5$ , and  $\sigma^2 = \text{var}(U) = 1/12$ . Thus,

$$P(|U - 0.5| \ge 2\sigma) = 2 \times P(U - 0.5 \ge \frac{2}{\sqrt{12}}) = 2 \times P(U \ge 1.077) = 0$$

Since 0 < 0.25, this result is in line with Chebyshev's inequality.

(d) If Y is a binomial random variable with n=10 and p=0.8, then  $\mu=E(Y)=np=8$ , and  $\sigma=\sqrt{\text{var}(Y)}=\sqrt{np(1-p)}=1.26491$ . Thus,

$$P(|Y - \mu| \ge 2\sigma) = P(Y - \mu \ge 2\sigma) + P(\mu - Y \ge 2\sigma)$$

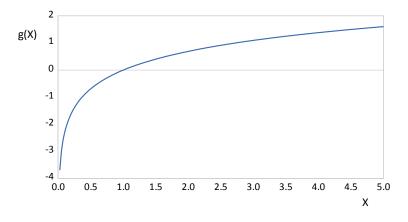
$$= P(Y \ge 8 + 2 \times 1.26491) + P(Y \le 8 - 2 \times 1.26491)$$

$$= P(Y \ge 10.5298) + P(Y \le 5.4702) = 0 + P(Y \le 5) = 0.03279$$

Since 0.03279 < 0.25, this result is in line with Chebyshev's inequality.

### **EXERCISE B.27**

(a) If  $g(X) = \ln(X)$ , then  $\frac{d^2g}{dX^2} = -\frac{1}{X^2}$ . Because  $\frac{d^2g}{dX^2} < 0$  for X > 0,  $g(X) = \ln(X)$  is concave for X > 0.



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- (b) E(X) = 3 and  $E[\ln(X)] = 1.0227$ . Since  $\ln(3) = 1.0986 > 1.0227$ , the inequality  $\ln[E(X)] \ge E[\ln(X)]$  is satisfied.
- (c)  $\ln\left(\sum_{i=1}^{4} x_i / 4\right) = \ln(2.5) = 0.9163$  and  $\sum_{i=1}^{4} \ln\left(x_i\right) / 4 = 0.7945$ . Hence,  $\ln\left(\sum_{i=1}^{4} x_i / 4\right) \ge \sum_{i=1}^{4} \ln\left(x_i\right) / 4$ .

- (a)  $P(X^2 \ge 5) = P(X \ge 3) = 0.7$  and  $E(X^2) = 10$ . Thus,  $P(X^2 \ge 5) = 0.7 \le E(X^2)/5 = 2$ .
- (b) When  $g(X) = (X \mu_X)^2$  and  $c = k^2 \sigma_X^2$ , Markov's Inequality  $P[g(X) \ge c] \le c^{-1} E[g(X)]$  becomes

$$P\left[\left(X - \mu_X\right)^2 \ge k^2 \sigma_X^2\right] \le \frac{\sigma_X^2}{k^2 \sigma_Y^2}$$

from which we obtain

$$P[|X - \mu_X| \ge k\sigma_X] \le \frac{1}{k^2}$$

Let  $\varepsilon = k\sigma_X$  so that  $1/k^2 = \sigma_X^2/\varepsilon^2$ , then we get Chebyshev's Inequality,

$$P[|X - \mu_X| \ge \varepsilon] \le \frac{\sigma_X^2}{\varepsilon^2}$$

#### **EXERCISE B.31**

(a) 
$$E(Y|X) = 1 \times x + 0 \times (1 - x) = x$$

$$E(Y) = E_X \left[ E(Y|X) \right] = \int_0^1 x f(x) dx = \frac{x^2}{2} \Big]_0^1 = \frac{1}{2}$$
(b) 
$$\operatorname{var}(Y|X) = E\left(Y^2|X\right) - \left[ E(Y|X) \right]^2 = 1^2 \times x + 0^2 \times (1 - x) - x^2 = x - x^2$$

$$\operatorname{var}(Y) = E_X \left[ \operatorname{var}(Y|X) \right] + \operatorname{var}_X \left[ E(Y|X) \right] = \int_0^1 (x - x^2) dx + \operatorname{var}_X(x)$$

Because *X* is a uniform random variable over the interval (0,1),  $var_X(x) = \frac{1}{12}$ . Thus,

$$\operatorname{var}(Y) = \left(\frac{x^2}{2} - \frac{x^3}{3}\right)\Big|_{0}^{1} + \frac{1}{12} = \frac{1}{2} - \frac{1}{3} + \frac{1}{12} = \frac{1}{4}$$