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STOCKHOLM UNIVERSITY  
Department of Statistics

Michael Carlson  
Emma Pettersson  
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## Solutions to Plenary Exercises: Plenary Exercise 7

Basic Statistics for Economists, 15 ECTS, STE101

### EXERCISE 1

There are two samples, one taken before and one after the police car. Assume that the speed of the cars are independent of each other.

The samples are not independent since it's the same car being measured at two different locations. The two samples show paired observations for the speed before ( $X$ ) and the speed after ( $Y$ ).

Assume that the difference  $D_i = X_i - Y_i$  is a random variable with observations that are independent and identically normally distributed  $D_i \sim N(\mu_D, \sigma_D)$ .

The mean difference  $\mu_D = \mu_X - \mu_Y$  and the variance  $\sigma_D^2$  are unknown and are estimated with the sample mean  $\bar{d}$  and sample variance  $s_d^2$ .

Hypotheses:

$$H_0: \mu_D = \mu_X - \mu_Y = 0$$

$$H_A: \mu_D = \mu_X - \mu_Y > 0$$

$$\alpha = 0.05$$

Test statistic:

$$t = \frac{\bar{d} - \mu_0}{s_d / \sqrt{n}} \sim t(d, f = n - 1)$$

Decision rule: we reject the null hypothesis if  $t_{obs} > t_c$ .

The critical value:

$$t_c = t_{n-1; \alpha} = t_{11; 0.05} = [\text{table 3}] = \mathbf{1.796}$$

Calculations and the observed value of the test statistic:

| Car no. | 1   | 2  | 3   | 4   | 5  | 6  | 7    | 8  | 9   | 10 | 11  | 12  | Sum  |
|---------|-----|----|-----|-----|----|----|------|----|-----|----|-----|-----|------|
| $x_i$   | 83  | 88 | 106 | 131 | 84 | 87 | 129  | 97 | 92  | 91 | 124 | 99  |      |
| $y_i$   | 61  | 84 | 95  | 121 | 83 | 79 | 92   | 88 | 69  | 90 | 115 | 100 |      |
| $d_i$   | 22  | 4  | 11  | 10  | 1  | 8  | 37   | 9  | 23  | 1  | 9   | -1  | 134  |
| $d_i^2$ | 484 | 16 | 121 | 100 | 1  | 64 | 1369 | 81 | 529 | 1  | 81  | 1   | 2848 |

Mean: 
$$\bar{d} = \frac{1}{n} \sum_{i=1}^n d_i = \frac{134}{12} = 11.167$$

Variance 
$$s_d^2 = \frac{\sum_{i=1}^n d_i^2 - n\bar{d}^2}{n-1} = \frac{2848 - 12(11.167^2)}{11} = 122.879$$

$$t_{obs} = \frac{\bar{d} - 0}{s_d/\sqrt{n}} = \frac{11.167}{\sqrt{122.879/12}} = \mathbf{3.49}$$

Conclusion:

We reject the null hypothesis since  $t_{obs} > t_c$ . The observed average speed after seeing the police car is significantly less than the average speed before the police car.

## EXERCISE 2

Let  $X$  represent car model 1 and  $Y$  represent car model 2.

Assumptions:

Two independent samples, each one with  $n_x = n_y = 64$  independent observations from unknown distributions with means  $\mu_X$  and  $\mu_Y$  and variances  $\sigma_X^2$  and  $\sigma_Y^2$  respectively.

Because both sample are large ( $n_X = n_Y > 30$ ), according to the CLT,  $\bar{X}$  and  $\bar{Y}$  are approximately normally distributed.  $\bar{X} \sim N(\mu_X, \sigma_X^2/n_X)$  and  $\bar{Y} \sim (\mu_Y, \sigma_Y^2/n_Y)$ .

Note that the text doesn't specify whether the variances given are the true population variances ( $\sigma_X^2$  and  $\sigma_Y^2$ ) or if they are the sample variances ( $S_X^2$  and  $S_Y^2$ ). However, since the samples are both large, we can use a z test, not knowing whether the variance is known or unknown isn't a problem.

Hypotheses:

$$H_0: \mu_X - \mu_Y = 0$$

$$H_A: \mu_X - \mu_Y \neq 0$$

$$\alpha = 0.05$$

Test variable:

$$Z = \frac{\bar{X} - \bar{Y} - D_0}{\sqrt{\frac{s_x^2}{n_x} + \frac{s_y^2}{n_y}}} \sim N(0,1)$$

Decision rule:

We reject the null hypothesis if  $|z_{obs}| > z_{\alpha/2}$ .

The critical value:

$$z_{\alpha/2} = [table 2] = 1.96$$

The observed value:

$$z_{obs} = \frac{\bar{x} - \bar{y}}{\sqrt{\frac{s_x^2}{n_x} + \frac{s_y^2}{n_y}}} = \frac{29.5 - 27.25}{\sqrt{\frac{6.37}{64} + \frac{5.44}{64}}} = 5.2378$$

Since  $z_{obs} > z_{\alpha/2}$ , we reject the null hypothesis. The observed average difference in the breaking power of cars 1 and 2 is significant.

We can also calculate the p-value:

$$\begin{aligned} p - \text{value} &= 2 P(Z > |z_{obs}|) = 2 P(Z > 5.2378) = 2(1 - P(Z \leq 5.2378)) \\ &= [\text{from excel using function NORM.S.DIST}(5.2378, \text{TRUE})] \\ &= 2(1 - (0.999999918749)) = 0.000000162502 \end{aligned}$$

We can also solve this problem in a more conservative way using a  $t$ -test:

Assumptions:

$X \sim N(\mu_X, \sigma_X^2)$  and  $Y \sim N(\mu_Y, \sigma_Y^2)$ . Also assume that  $\sigma_Y^2 = \sigma_X^2$ ; we have two estimates for the same variance, so we pool  $s_x^2$  and  $s_y^2$  to estimate  $s_p^2$ .

The test variable:

$$t_{126} = \frac{\bar{X} - \bar{Y}}{s_p \sqrt{\frac{1}{n_x} + \frac{1}{n_y}}} \sim t(df = n_x + n_y - 2)$$

Decision rule:

We reject the null hypothesis if  $|t_{obs}| > t_c$ .

The critical value:

$$t_c = t_{n_x+n_y-2; \alpha/2} = t_{126; 0.025} = [table\ 3] = 1.979$$

The observed value:

$$s_p^2 = \frac{(n_x - 1)s_x^2 + (n_y - 1)s_y^2}{n_x + n_y - 2} = \frac{(63)(6.37 + 5.44)}{126} = \frac{6.37 + 5.44}{2} = 5.905$$
$$t_{obs} = \frac{\bar{X} - \bar{Y}}{s_p \sqrt{\frac{1}{n_x} + \frac{1}{n_y}}} = \frac{29.5 - 27.25}{\sqrt{5.905} \sqrt{2/64}} = 5.2378$$

Conclusion:

We reject the null hypothesis since  $t_{obs} > t_c$ . Observe that we got the same value for  $t_{obs}$  and  $z_{obs}$ . This is because the size of the both samples were equal, if they had been different we would have gotten different values. The only difference is that the critical value of the  $t$ -test is larger, the  $t$ -test is more conservative as it makes it more difficult to reject the null hypothesis.

The  $p$ -value becomes larger (using the function `=2*T.DIST.RT(5.2378,126)` in Excel):

$$p - value = 2 P(t > |t_{obs}|) = 2(t > 5.2378) = 0.0000006614$$

### EXERCISE 3

The proportions we want to test:

$$\begin{aligned} \text{Car} & P_C = \frac{1}{2} \\ \text{Public Transport} & P_P = \frac{2}{3} \times \frac{1}{2} = \frac{1}{3} \\ \text{Bicycle} & P_B = \frac{1}{3} \times \frac{1}{2} = \frac{1}{6} \end{aligned}$$

Goodness of fit test:

Hypotheses:

$$H_0: P_C = \frac{1}{2}, P_P = \frac{1}{3}, P_B = \frac{1}{6}$$

$H_A$ : The null hypothesis distribution does not hold, at least one of the statements above is false.

$$\alpha = 0.05$$

Test statistic:

$$\chi^2 = \sum \frac{(O_i - E_i)^2}{E_i} \sim \chi_{k-1}^2$$

Decision rule:

We reject the null hypothesis if  $\chi_{obs}^2 > \chi_{k-1;\alpha}^2$ .

The critical value:

$$\chi_{k-1;\alpha}^2 = \chi_{2;0.05}^2 = 5.991$$

The observed value:

| $i$                         | Car           | Public Transport | Bicycle       | Sum                                     |
|-----------------------------|---------------|------------------|---------------|---|
| $P_i$                       | $\frac{1}{2}$ | $\frac{1}{3}$    | $\frac{1}{6}$ | 1                                       |
| $E_i = nP_i$                | 25            | 16.667           | 8.333         | 50                                      |
| $O_i$                       | 22            | 14               | 14            | 50                                      |
| $(O_i - E_i)$               | -3            | -2.6667          | 5.66667       | 0                                       |
| $(O_i - E_i)^2$             | 9             | 7.11111          | 32.1111       |   |
| $\frac{(O_i - E_i)^2}{E_i}$ | 0.36          | 0.42667          | 3.85333       | <b><math>\chi_{obs}^2 = 4.64</math></b> |

Conclusion:

We cannot reject the null hypothesis  $\chi_{2;0.05}^2 > \chi_{obs}^2$ . The observed frequencies are not significantly different from the hypothesized distribution.

## EXERCISE 4

Hypotheses:

$H_0$ : The data collection method and non response are **independent**

$H_A$ : The data collection method and non response are **dependent**

Test statistic:

$$\chi^2 = \sum_{i=1}^r \sum_{j=1}^c \frac{(O_{ij} - E_{ij})^2}{E_{ij}} \sim \chi^2(df = (r-1)(c-1))$$

$E_{ij} = \frac{R_i C_j}{n}$ , Where  $R_i$  is the row sum and  $C_j$  is the column sum.  $r$  is the number of rows, and  $c$  is the number of columns.

We reject the null hypothesis if  $\chi_{obs}^2 > \chi_{2;0.05}^2$ .

The critical value:

$$\chi_{2;0.05}^2 = 5.991$$

The observed value:

| $O_{ij}$     | MM  | CATI | PAPI | Sum  |
|--------------|-----|------|------|------|
| Response     | 264 | 297  | 320  | 881  |
| Non-Response | 110 | 72   | 145  | 327  |
| Sum          | 374 | 369  | 465  | 1208 |

| $E_{ij}$     | MM       | CATI     | PAPI     | Sum  |
|--------------|----------|----------|----------|------|
| Response     | 272.7599 | 269.1134 | 339.1267 | 881  |
| Non-Response | 101.2401 | 99.88659 | 125.8733 | 327  |
| Sum          | 374      | 369      | 465      | 1208 |

| $(O_{ij} - E_{ij})^2 / E_{ij}$ | MM       | CATI     | PAPI     | Sum             |
|--------------------------------|----------|----------|----------|-----------------|
| Response                       | 0.281333 | 2.889718 | 1.078738 | 4.24979         |
| Non-Response                   | 0.757965 | 7.785448 | 2.906326 | 11.44974        |
|                                |          |          |          | <b>15.69953</b> |

$$\chi_{obs}^2 = \sum_{i=1}^r \sum_{j=1}^c \frac{(O_{ij} - E_{ij})^2}{E_{ij}} = 15.69953$$

Conclusion:

We reject the null hypothesis on the 5% significance level since the observed value is larger than the critical value. The level of non-response is dependent on the interview type.

## EXERCISE 5

Hypotheses:

$H_0$ : App experience and phone brand are independent

$H_A$ : App experience and phone brand are dependent

$$\alpha = 0.05$$

Test statistic:

$$\chi^2 = \sum_{i=1}^r \sum_{j=1}^c \frac{(O_{ij} - E_{ij})^2}{E_{ij}} \sim \chi^2(df = (r-1)(c-1))$$

where  $E_{ij} = \frac{R_i C_j}{n}$ ,  $R_i$  is the row sum and  $C_j$  is the column sum.  $r$  is the number of rows and  $c$  is the number of columns.

Decision rule:

Reject  $H_0$  if  $\chi_{obs}^2 > \chi_c^2$

Critical value:

$$\chi_c^2 = \chi_{(r-1)(c-1), \alpha}^2 = \chi_{1, 0.05}^2 = \mathbf{3.841}$$

Observed value:

| $O_{ij}$      |     | Has iPhone |    | $\Sigma$ |
|---------------|-----|------------|----|----------|
|               |     | Yes        | No |          |
| Likes the app | Yes | 80         | 25 | 105      |
|               | No  | 80         | 15 | 95       |
| $\Sigma$      |     | 160        | 40 | 200      |

| $E_{ij}$      |     | Has iPhone |    | $\Sigma$ |
|---------------|-----|------------|----|----------|
|               |     | Yes        | No |          |
| Likes the app | Yes | 84         | 21 | 105      |
|               | No  | 76         | 19 | 95       |
| $\Sigma$      |     | 160        | 40 | 200      |

| $\frac{(O_{ij} - E_{ij})^2}{E_{ij}}$ |     | Has iPhone |         |  |
|--------------------------------------|-----|------------|---------|--|
|                                      |     | Yes        | No      |  |
| Likes the app                        | Yes | 0.19048    | 0.76191 | $\Sigma = \chi_{obs}^2 = \mathbf{2.005}$ |
|                                      | No  | 0.21053    | 0.84211 |  |

Since  $\chi_{obs}^2 < \chi_c^2$  we cannot reject  $H_0$  on the 5% significance level. The app experience and the phone brand are independent.

## EXERCISE 6

- a. The first step is to calculate the moving averages. Because we have quarterly data ( $s = 4$ ), we calculate 4-point moving averages. Then we calculate the average of two adjacent averages.

For example, for  $t = 3$  we first calculate  $x_{2.5}^*$  and  $x_{3.5}^*$ , then  $x_3^*$ .

$$x_{2.5}^* = \frac{x_1 + x_2 + x_3 + x_4}{4} = \frac{16913.6}{4} = 4228.4$$

$$x_{3.5}^* = \frac{x_2 + x_3 + x_4 + x_5}{4} = \frac{16988.3}{4} = 4247.1$$

$$x_3^* = \frac{x_{2.5}^* + x_{3.5}^*}{2} = \frac{\frac{x_1 + x_2 + x_3 + x_4}{4} + \frac{x_2 + x_3 + x_4 + x_5}{4}}{2} = \frac{x_1}{8} + \frac{x_2}{4} + \frac{x_3}{4} + \frac{x_4}{4} + \frac{x_5}{8} = 4237.738$$

We do this for all observations except the first two ( $t = 1$  and 2) and last two in the series ( $t = 11$  and 12), those are instead marked with an '\*' symbol in the table below. In total you should calculate 12 moving averages from  $x_3^*$  to  $x_{14}^*$ .

After that, the next step is to calculate the ratio between the observed values and the moving averages. We want to see if a seasonal effect causes a consistent percentage increase or decrease in the different quarters.

$$q_t = 100 \cdot \frac{x_t}{x_t^*} \text{ for } t = 3, \dots, 10$$

| Year/quarter | $t$ | $x_t$   | $x_t^*$    | $q_t$    |
|--------------|-----|---------|------------|----------|
| 2014Q1       | 1   | 4 119.8 | *          | *        |
| 2014Q2       | 2   | 4 239.7 | *          | *        |
| 2014Q3       | 3   | 4 329.6 | 4 237.7375 | 102.1677 |
| 2014Q4       | 4   | 4 224.5 | 4 254.2000 | 99.3019  |
| 2015Q1       | 5   | 4 194.5 | 4 267.4375 | 98.2908  |
| 2015Q2       | 6   | 4 296.7 | 4 285.0500 | 100.2719 |
| 2015Q3       | 7   | 4 378.5 | 4 307.8375 | 101.6403 |
| 2015Q4       | 8   | 4 316.5 | 4 333.5750 | 99.6060  |
| 2016Q1       | 9   | 4 284.8 | 4 356.1375 | 98.3624  |
| 2016Q2       | 10  | 4 412.3 | 4 373.3375 | 100.8909 |
| 2016Q3       | 11  | 4 443.4 | *          | *        |
| 2016Q4       | 12  | 4 389.2 | *          | *        |

In the next step, we group the ratios ( $q_t$ ) according to quarter and calculate the median ratio for each quarter. Then, to guarantee that the mean of the seasonal index will be 100%, we need to make adjustments so that the de-seasoned values aren't too large or small. The sum of the medians was 400.00266, so we adjust using:



$$\text{Index}_Q = \text{Median} \cdot \frac{400}{400.00266}$$

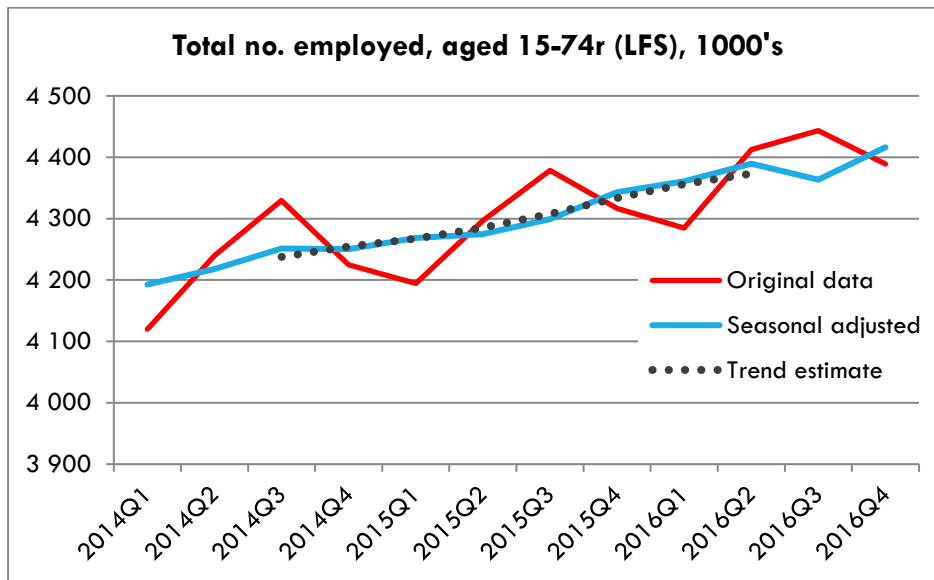
|     | 2014    | 2015    | 2016    | Median  | Index   |
|-----|---------|---------|---------|---------|---------|
| Q1  | *       | 0.98291 | 0.98362 | 0.98327 | 0.98261 |
| Q2  | *       | 1.00272 | 1.00891 | 1.00581 | 1.00515 |
| Q3  | 1.02168 | 1.01640 | *       | 1.01904 | 1.01836 |
| Q4  | 0.99302 | 0.99606 | *       | 0.99454 | 0.99388 |
| Sum |         |         |         | 4.00266 | 4       |

The last step is to calculate the de-seasoned values  $x_t^{adj}$  by multiplying the original  $x_t$  with 100 and dividing by the seasonal index.

$$x_t^{adj} = x_t \times \frac{100}{\text{Index}_Q}$$

| Year/Quarter | $t$ | $x_t$  | $\text{Index}_Q$ | De-seasoned |
|--------------|-----|--------|------------------|-------------|
| 2014Q1       | 5   | 4119.8 | 98.261           | 4 192.70    |
| 2014Q2       | 6   | 4239.7 | 100.515          | 4 218.00    |
| 2014Q3       | 7   | 4329.6 | 101.836          | 4 251.53    |
| 2014Q4       | 8   | 4224.5 | 99.388           | 4 250.52    |
| 2015Q1       | 9   | 4194.5 | 98.261           | 4 268.72    |
| 2015Q2       | 10  | 4296.7 | 100.515          | 4 274.70    |
| 2015Q3       | 11  | 4378.5 | 101.836          | 4 299.55    |
| 2015Q4       | 12  | 4316.5 | 99.388           | 4 343.09    |
| 2016Q1       | 13  | 4284.8 | 98.261           | 4 360.62    |
| 2016Q2       | 14  | 4412.3 | 100.515          | 4 389.71    |
| 2016Q3       | 15  | 4443.4 | 101.836          | 4 363.28    |
| 2016Q4       | 16  | 4389.2 | 99.388           | 4 416.23    |

- b. A time series diagram with both the original and the de-seasoned series.



We see that the seasonally adjusted series is almost a straight line with a positive trend but with small random fluctuations towards the end of the series where there is an unexpected decrease for quarter 3 in 2016.

Comments, what we have done:

First we assumed the series can be described using a multiplicative model:

$$X_t = T_t S_t I_t$$

The first step was to calculate a moving average that gives an estimated of the trend  $T_t$  for 12 time points  $t = 3 \dots 14$

$$\hat{T}_t = x_t^* = \frac{x_{t-2}}{8} + \frac{x_{t-1}}{4} + \frac{x_t}{4} + \frac{x_{t+1}}{4} + \frac{x_{t+2}}{8}$$

By dividing the observed values with the moving average we are left with the seasonal and irregular parts.

$$\frac{x_t}{x_t^*} = \frac{x_t}{\hat{T}_t} = \frac{T_t S_t I_t}{\hat{T}_t} \approx S_t I_t$$

In the next step we gathered the values according to quarter and the median for each quarter was used as an estimate of the seasonal component  $\hat{S}_Q$ . We then adjusted these medians so the mean of the seasonal index is 1 (or 100%).

When the seasonal indices for the different quarters are ready we can then calculated the seasonally adjusted values that show the trend and irregular component.

$$\frac{x_t}{\hat{S}_Q} = \frac{T_t S_Q}{\hat{S}_Q} \approx T_t I_t$$