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# AFRE 802 Statistical Methods for Agricultural, Food, & Resource Economists



Hypothesis Testing – Part 3 of 3 (WMS Ch. 10.4, 10.10, 10.12)

November 16, 2017

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### **GAME PLAN**

- Housekeeping issues
  - Ch. 10 HW due Tuesday, 11/28
- Review
- Graded in-class exercise
- Hypothesis testing Part 3 of 3
  - Hypothesis testing with  $\chi^2$  and F statistics
  - Calculating Type II error probabilities and finding the sample size for Z tests
  - · The "power" of statistical tests
  - · Wrap-up of Chapter 10

### Review: Hypothesis testing

- Steps essentially the same for large sample hypothesis testing and small sample hypothesis testing about μ but *key difference* is:
  - Large sample tests: can invoke CLT & use Z-stat ~ N(0,1)
  - Small sample tests for  $\mu$ : use T-stat ~ t with N-1 d.f.; data need to be from approximately normal distribution

### Review: Relationship b/w Cls & hypothesis testing

- If testing  $H_0$ :  $\theta = \theta_0$  vs.  $H_1$ :  $\theta \neq \theta_0$ 
  - Fail to reject  $H_0$  in favor of  $H_1$  at the  $\alpha$  level if  $\theta_0$  lies inside the 100(1- $\alpha$ )% two-sided CI; o.w. reject  $H_0$
- If testing H<sub>0</sub>: θ=θ<sub>0</sub> vs. H<sub>1</sub>: θ>θ<sub>0</sub> (implicitly H<sub>0</sub>: θ≤θ<sub>0</sub>)
  - Fail to reject  $H_0$  in favor of  $H_1$  at the  $\alpha$  level if  $\theta_0$  lies inside the 100(1- $\alpha$ )% lower one-sided CI; o.w. reject  $H_0$
- If testing H₀: θ=θ₀ vs. H₁: θ<θ₀ (implicitly H₀: θ≥θ₀)</li>
  - <u>Fail to reject</u> H<sub>0</sub> in favor of H<sub>1</sub> at the α level if θ<sub>0</sub> lies <u>inside</u> the 100(1-α)% <u>upper one-sided</u> CI; o.w. reject H<sub>0</sub>

SEE HANDOUT FROM LAST CLASS FOR DETAILS 2

### Review: p-values

- Definition?
  - **p-value** = the smallest  $\alpha$  for which the data suggest the null hypothesis should be rejected (in favor of the alternative)
  - The probability of observing a test "statistic as extreme as we did if the null hypothesis is true" (Wooldridge 2003, p. 129)
- Which is better if want to reject H<sub>0</sub> small or large p-value?
  - The smaller the p-value, the stronger is the evidence <u>against</u> the null (in favor of the alternative)
- How to find the p-value for a test statistic?
  - Follow the usual hypothesis testing steps but rather than picking  $\alpha$  and identifying the rejection region, determine the significance level of your test statistic (keeping the alternative hypothesis in mind and thus whether you are dealing with an " $\alpha$ " or " $\alpha$ /2" situation)
  - EX) 2-sided alternative and Z-stat: p=2\*P(z > |Z-stat|)
  - EX) 1-sided alternative and Z-stat: p=P(z > |Z-stat|)
  - Similar for T (with appropriate D.F.) because also symmetric
- Suppose you are conducting a hypothesis test at a given α level. What do you conclude if p≤α? What if p>α?

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### Graded in-class exercise

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## Hypothesis testing with $\chi^2$ and F statistics

- We've now worked a lot with Z and t statistics but we don't have enough time in this course to do more hypothesis testing that involves x² and F statistics
- But you'll encounter these more next semester & beyond
- Examples of hypothesis tests with test statistics  $\sim \chi^2$ 
  - Testing hypotheses about the variance of one normal RV
  - The Jarque-Bera test for normality
  - · Ljung-Box Q test for autocorrelation
  - Likelihood ratio tests (hypothesis testing for MLE)
- Applications of F distributions
  - Testing hypotheses about the variances of two normal RVs
  - · Joint hypothesis testing in regression analysis, e.g.,

$$y=\beta_0+\beta_1x_1+\beta_2x_2+u$$
  
 $H_0: \beta_1=\beta_2=0$  vs.  $H_4: \beta_1\neq 0$  and/or  $\beta_2\neq 0$ 

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### Calculating the probability of Type II error $(\beta)$

- Very difficult for some statistical tests but pretty straightforward for the large-sample tests we covered (Z-stat-based)
- Review: what is type II error?
  - Failing to reject  $H_0$  (in favor of  $H_1$ ) when  $H_0$  is false
- When calculating β=P(Type II error), must do so for specific values of the target parameter under H<sub>1</sub>
  - E.g., if testing H<sub>0</sub>: μ=5 vs. H<sub>1</sub>: μ > 5, need to pick a specific value of μ > 5 (e.g., 6, 100, whatever)
- Let's work through an example then go over some general rules for finding β=P(Type II error)

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# Calculating the probability of Type II error $(\beta)$

#### Example 10.8 in WMS

Suppose we tested  $H_0$ :  $\mu$ =15 vs.  $H_1$ :  $\mu$  > 15 at the  $\alpha$ =0.05 level using data from a random sample of size N=36 with sample mean 17 and sample standard deviation 3. (Context is the average # of calls/week made by salespeople at a large corporation.)

- a. We obtain Z=4.  $z_{\alpha=0.05}=1.645$  so do we reject or fail to reject  $H_0$  in favor of  $H_1$ ? What is the p-value for our test?
- b. Now suppose we want to know  $\beta$ =P(Type II error) for testing H<sub>0</sub>:  $\mu$ =15 vs. H<sub>1</sub>:  $\mu$  = 16 given  $\alpha$ =0.05.

#### Steps:

- 1. Find the cutoff for the RR in terms of Z (under  $H_0$  and for the given  $\alpha$ ), then express it in terms of  $\overline{Y}$ . Let k be this cutoff value for  $\overline{Y}$ .
- 2.  $P(\text{Type II error}) = P(\text{fail to reject H}_0 \text{ in favor of H}_1 \text{ when H}_0 \text{ is false and H}_1 \text{ is true})$ 
  - =  $P(\overline{Y} \text{ is } \underline{\text{not}} \text{ in the rejection region when H}_0 \text{ is false and H}_1 \text{ is true})$
  - =  $P(\overline{Y} \le k \text{ when } H_0 \text{ is false and } H_1 \text{ is true})$
  - $\Rightarrow$  Find this probability by converting  $\overline{Y} = k$  to a Z-statistic **under H**<sub>1</sub>.

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 $\alpha$ =P(Type I error)=P(reject H<sub>0</sub> when H<sub>0</sub> is true) Example 10.8  $\beta$ =P(Type II error)=P(fail to reject H<sub>0</sub> when H<sub>0</sub> is false (cont'd) and H<sub>1</sub> is true given specific values of H<sub>1</sub> and α) =  $P(\overline{Y} \text{ is } \underline{\text{not}} \text{ in the rejection region when H}_0 \text{ is false and H}_1 \text{ is true})$ =  $P(\overline{Y} \le k \text{ when } H_0 \text{ is false and } H_1 \text{ is true}))$  $\mu_0 = 15$  $16 = \mu_a$ Accept  $H_0$ Reject  $H_0$ k=15.8225 is the cutoff for the sample mean for our rejection region for H<sub>0</sub>:  $\mu$ =15 vs. H<sub>1</sub>:  $\mu$  > 15 (specifically  $\mu$  = 16) at the  $\alpha$ =0.05 level. That is, we reject H<sub>0</sub> in favor of H<sub>1</sub> if the sample mean is ≥ 15.8225.

### Calculating $\beta$ =P(Type II error)

General approach for  $H_0$ :  $\theta = \theta_0$  vs.  $H_1$ :  $\theta > \theta_0$  for a specific value of the target parameter under  $H_1$  (call it  $\theta_1$ , where  $\theta_1 > \theta_0$ )

- 1. Find the cutoff for the RR in terms of Z (**under H**<sub>0</sub> and for the **given**  $\alpha$ ), then express it in terms of the estimator,  $\hat{\theta}$ . Let k be this cutoff value for  $\hat{\theta}$ , i.e.:  $RR = [k, \infty)$
- 2.  $P(\text{Type II error}) = P(\text{fail to reject H}_0 \text{ in favor of H}_1 \text{ when H}_0 \text{ is false and H}_1 \text{ is true})$ =  $P(\hat{\theta} \text{ is not in the rejection region when H}_0 \text{ is false and H}_1 \text{ is true})$ =  $P(\hat{\theta} \le k \text{ when H}_0 \text{ is false and H}_1 \text{ is true, i.e., when } \theta = \theta_1)$

Find this probability by converting k to a Z-statistic **under H**<sub>1</sub>, i.e.:

$$P(z \le Z = \frac{k - \theta_1}{\sigma_{\hat{\theta}}})$$

Note: Will need to reverse signs in the steps above if  $H_1$ :  $\theta \le \theta_0$ 

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# Another example

Suppose N=40, sample mean = 128.6, and sample standard deviation is 2.1. Find the probability of type II error for testing  $H_0$ :  $\mu$ =130 vs.  $H_1$ :  $\mu$  = 128 given  $\alpha$ =0.05.

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## Finding the sample size for Z-tests

- In Example 10.8, with N=36 and  $\alpha$ =0.05, we calculated that  $\beta$ =0.36  $\rightarrow$  high P(Type II error)
- A key way to reduce  $\beta$  is to increase the sample size
- The flip side of determining β given N and α is to determine N given desired values of α and β
- Suppose you want to test  $H_0$ :  $\mu = \mu_0$  vs.  $H_1$ :  $\mu > \mu_0$  for given values of  $\alpha$  and  $\beta$  (and where  $\beta$  is evaluated at specific value  $\mu_1 > \mu_0$  under  $H_1$ ). Then:

Sample size for a one-tailed Z-test for  $\mu$  for given levels of  $\alpha$ ,  $\beta$ ,  $\mu_0$  (value of  $\mu$  under  $H_0$ ) and  $\mu_I$  (value of  $\mu$  under  $H_I$ ):  $N = \frac{(z_{\alpha} + z_{\beta})^2 \sigma^2}{(\mu_I - \mu_0)^2}$  rounded up to the nearest whole number

Same formula works for  $H_1$ :  $\mu < \mu_0$ . See WMS p. 509 for proof.

## Finding the sample size for Z-tests - example

#### Example 10.9 in WMS

Find the sample size, N, for testing  $H_0$ :  $\mu$ =15 vs.  $H_1$ :  $\mu$ =16 with  $\alpha$ = $\beta$ =0.05. Assume a variance of 9. (Context is the average # of calls/week made by salespeople at a large corporation.)

Sample size for a one-tailed Z-test for  $\mu$  for given levels of  $\alpha$ ,  $\beta$ ,  $\mu_0$  (value of  $\mu$  under  $H_0$ ) and  $\mu_I$  (value of  $\mu$  under  $H_I$ ):

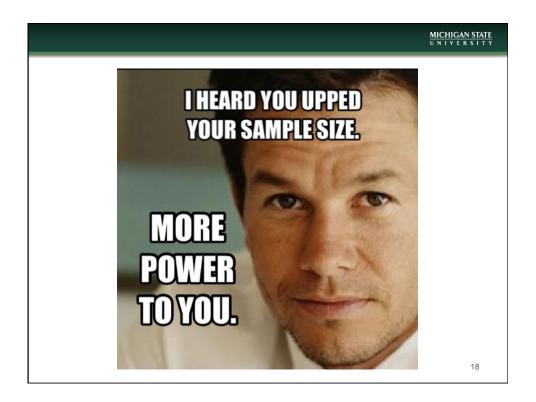
$$N = \frac{(z_{\alpha} + z_{\beta})^2 \sigma^2}{(\mu_I - \mu_0)^2}$$
 rounded up to the nearest whole number

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# The "power" of statistical tests

- We have discussed β=P(Type II Error)
   =P(fail to reject H<sub>0</sub> when H<sub>0</sub> is false and H<sub>1</sub> is true)
- The "power" of a statistical test is 1-β, i.e., the probability that we do reject H<sub>0</sub> when H<sub>0</sub> is false and H<sub>1</sub> is true. More power is better than less power!
  - As with  $\beta$ , the power of a test depends on the parameter value specified under  $H_1(\theta_1)$
- How does β change as N increases?
- So how does power change as N increases?



# The "power" of statistical tests (cont'd)

- · Final note on power:
  - Do you think statistical tests have more power for parameter values under  $H_1(\theta_1)$  that are close to or farther away from the value under the  $H_0(\theta_0)$ ? Why?
  - It is easier to detect that  $H_0$  is false (more power) when  $\theta_1$  is  $\underline{\text{\bf farther}}$  from  $\theta_0$

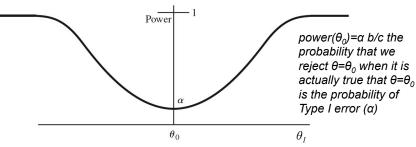


Figure: A typical power curve for the test of  $H_0$ :  $\theta=\theta_0$  vs.  $H_1$ :  $\theta=\theta_1$  for various values of  $\theta_1$ 

### Summary

- In Chapters 8 and 9, we talked about how to estimate numerical values of target parameter θ
  - Point estimates & confidence intervals (CIs)
  - Desirable properties of estimators (consistency, unbiasedness, efficiency, low MSE)
  - Methods of estimation (MOM, MLE, least squares)
- In Chapter 10, we talked about:
  - Testing hypotheses related to  $\theta$  for large samples, and for  $\mu$  for small samples
  - The relationship between hypothesis testing and CIs
  - p-values
  - Probabilities of Type I (α) and Type II (β) errors, and the power of a statistical test (1-β) → these probabilities tell us how 'good' our inferences are (i.e., how much faith we can put in the results of our hypothesis tests)
  - · Computing the sample size for Z tests

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### Homework:

- WMS Ch. 10 (cont'd):
  - Type II error probabilities & sample size for Z tests: 10.38, 10.39, 10.41, 10.42
- \*\*All Ch. 10 HW is due on Tuesday, Nov. 28

### Remaining lectures – only 5 left – time flies!

- Tuesday: Review, answer your questions; tie up Ch. 10 loose ends
- 4 classes after Thanksgiving break: introduction to OLS (hurray!) and course wrap-up

### Reading for Tuesday after break

- Optional: WMS Ch. 11 (sections 11.1-11.3)
- Required: Wooldridge Introductory Econometrics (2003) pp. 22-37 – on D2L

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Table 8.1 Expected values and standard errors of some common point estimators							
Target Parameter	Sample	Point Estimator	Square of varia of estin	nce Error			
$\theta$	Size(s)	$\hat{ heta}$	$E(\hat{\theta})$	$\sigma_{\hat{ heta}}$			
$\mu$	n	$\overline{Y}$	$\mu$	$\frac{\sigma}{\sqrt{n}}$			
p	n	$\hat{p} = \frac{Y}{n}$	p	$\sqrt{\frac{pq}{n}}$			
$\mu_1 - \mu_2$	$n_1$ and $n_2$	$\overline{Y}_1 - \overline{Y}_2$	$\mu_1 - \mu_2$	$\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}^{*\dagger}$			
$p_1 - p_2$	$n_1$ and $n_2$	$\hat{p}_1 - \hat{p}_2$	$p_1 - p_2$	$\sqrt{\frac{p_1 q_1}{n_1} + \frac{p_2 q_2}{n_2}}^{\dagger}$			

 $<sup>^{\</sup>dagger}\sigma_{1}^{2}$  and  $\sigma_{2}^{2}$  are the variances of populations 1 and 2, respectively.  $^{\dagger}$ The two samples are assumed to be independent.

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