

## TOPIC 5: HIPOTHESIS TESTING

### 5.1. KEY ISSUES

- ❖ A hypothesis test is a statistical method allowing to choose between two alternatives regarding the behaviour of the random variable under study.
- ❖ When the goal consists in giving values to the unknown parameters in the population, we will use parametric tests (topic 5).
- ❖ When the hypothesis concern other aspects of the variable, such as the probability distribution or sample features (independence and homogeneity) we will employ nonparametric tests (topic 6).
  
- ❖ General approach:
  - Let  $\xi$  be a random variable with probability distribution  $f(x;\theta)$   $\theta$  being an unknown parameter.
  - Then we formulate a null hypothesis  $H_0$  over the value of the parameter, for instance,  $H_0: \theta = \theta_0$  against an alternative hypothesis  $H_1: \theta \neq \theta_0$
  - Later on we take a s.r.s. and based on the point estimator  $\theta^*$  we elaborate a decision rule in order to accept or reject  $H_0$ .

- ❖ The hypothesis are established by the researcher following some criterion (look at point 1 in section 5.2)
- ❖ Then data are collected and hypothesis are tested with the sample with the purpose of choosing one of them.
- ❖ In the decision making process four situations may arise depending on which hypothesis is true or false:

	States of nature (reality)	
Decision	$H_0$ true	$H_0$ false
Accept $H_0$ (Reject $H_1$ )	Correct decision $1-\alpha$ (Confidence level)	Type II Error $\beta = P(\text{Accept } H_0 / H_0 \text{ false})$
Reject $H_0$ (Accept $H_1$ )	Type I Error $\alpha = P(\text{Reject } H_0 / H_0 \text{ true})$ (Significance level)	Correct decision $1-\beta$ (Power of the contrast)

- ❖ We would like  $\alpha$  and  $\beta$  be as small as possible. However, for a given sample, a reduction in  $\alpha$  involves an increase in  $\beta$  and viceversa, except when enlarging the sample size  $n$  at the same time.
- ❖ The choice between controlling  $\alpha$  or  $\beta$  depends on the cost arising from incurring in type I error or type II error, respectively
- ❖ Nevertheless, we usually prefer to fix  $\alpha$  in a low level and choose, among all possible tests for that  $\alpha$ , that one with the smallest  $\beta$  (hence, with the highest power)

## TYPE OF HYPOTHESIS

- ❖ Hypothesis are conjectures made about the value of some unknown parameter of a given population.
- ❖ There are two kind of hypothesis: single and composite
  - a. Single hypothesis specify a unique value for the parameter. In these cases the density function of the variable is completely determined.
  - b. Composite hypothesis assign a range of values to the unknown parameter.
- ❖ Under another point of view, the null hypothesis must be differentiated from the alternative one.
  - a. The null hypothesis  $H_0$  is established first and will be kept true unless data gathered from a s.r.s. shows strong evidence against that. However, to accept the null hypothesis doesn't mean it is correct, just that data do not offer strong evidence to reject it.
  - b. The alternative hypothesis  $H_1$  is that one accepted when the null hypothesis  $H_0$  is rejected.

❖ Possible ways to establish a hypothesis testing:

I	$H_0 : \theta = \theta_0$ $H_1 : \theta \neq \theta_0$	
II	$H_0 : \theta = \theta_0$ $H_1 : \theta < \theta_0$	$H_0 : \theta \geq \theta_0$ $H_1 : \theta < \theta_0$
III	$H_0 : \theta = \theta_0$ $H_1 : \theta > \theta_0$	$H_0 : \theta \leq \theta_0$ $H_1 : \theta > \theta_0$

- ❖ If the possible direction of the alternative hypothesis is known, then a one-tailed test will be formulated (cases II and III), otherwise a two-tailed test will apply (case I)

## 5.2. METHODOLOGY

To carry out a hypothesis testing we must follow some steps:

1.- To formulate both, the null hypothesis  $H_0$  and the alternative hypothesis  $H_1$

*General rule:* The researcher chooses as alternative hypothesis  $H_1$  what he or she considers true, this is, that one including the real value for the parameter.

Particular situations:

- ❖ In a risky context, the conjecture provoking the highest risk if it is rejected being true must appear as the null hypothesis  $H_0$ . The reason is that we control that risk through  $\alpha$ .
- ❖ Sometimes the researcher believes the parameter being either higher or lower than certain value. Then that conjecture appears as the alternative hypothesis  $H_1$ . In this situation, the researcher thinks  $H_1$  is true in the sense that it incorporates the value of the unknown parameter.
- ❖ Often the researcher tests a single value for the unknown parameter (with or without information). In such a case, that conjecture appears in the null hypothesis  $H_0$ .

In any context, the researcher will accept (not reject) the null hypothesis  $H_0$  unless data provide strong evidence against it, hence accepting the alternative hypothesis  $H_1$ .

## 2.- To determine the test statistic

- ❖ It is the statistic to be used in order to accept or reject the null hypothesis  $H_0$ .
- ❖ Such statistic must incorporate the discrepancy existing between the sample (represented by the point estimator  $\theta^*$ ) and the null hypothesis  $H_0$  (represented by the value  $\theta_0$  taken by the parameter in that hypothesis):

$$d(\theta_0; \theta^*) \equiv d$$

- ❖ The test statistic must follow a known probability distribution when  $H_0$  is true.

## 3.- To establish the level of significance $\alpha$ and determine the critical region

$$\alpha = P(\text{Reject } H_0 / H_0 \text{ true})$$

- ❖ Critical region is the interval or intervals in  $R$  in which the discrepancy between the sample and  $H_0$  is large enough as to reject  $H_0$
- ❖ When will the discrepancy be large enough?

Answer: when such discrepancy has a low probability to happen if  $H_0$  is true

That probability is the level of significance and is represented by  $\alpha$ :

$$P(d > d_c / H_0 \text{ true}) = \alpha$$

$d_c$  is called *critical value*

$\alpha$  is established by the researcher, usually 5% or 1%

- ❖ Those intervals in R being complementary to the critical region are called acceptance region.

The position of both regions depending on the hypothesis (one-tail or two-tails)

#### 4.- To select a s.r.s., to calculate the value of the test statistic and make a decision

In this stage data are collected and the estimate of the test statistic, which we will denote as  $d_0$  is obtained. Then a decision must be made:

- If that estimate ( $d_0$ ) falls inside the acceptance region, then the discrepancy between the sample and the null hypothesis  $H_0$  is not considered large enough and  $H_0$  is accepted (not rejected)
- On the contrary if such estimate ( $d_0$ ) falls inside the critical region, then the discrepancy is considered large enough and  $H_0$  is rejected ( $H_1$  is accepted)

### OTHER CONCEPTS

#### *p-value*

- ❖ The determination of the critical region through the significant level  $\alpha$  has some limitations

By one side, the decision making depends strongly on the level of  $\alpha$ . Hence, the researcher may reject the null hypothesis  $H_0$  for

$\alpha = 5\%$  but accept the same  $H_0$  for  $\alpha = 2\%$ .

By another side, the result of the test does not inform of the degree of strength used to reject  $H_0$ .

The procedure referred to as *p-value* allows to overcome these difficulties.

- ❖ The *p-value* is the probability of obtaining a discrepancy at least as extreme as that one observed in the sample when the null hypothesis  $H_0$  is true.

The discrepancy observed in the sample being  $d_0$  the estimate of the test statistic. Therefore:

$$p - value = P(d \geq d_0 / H_0)$$

The lower the *p-value*, the smaller the probability to find a discrepancy as extreme as that one observed under the null hypothesis and, therefore, the lower the likelihood of  $H_0$  (Peña, D.).

The *p-value* can also be interpreted as the sampling significant level, meaning that it is the probability of rejecting the null hypothesis  $H_0$  when the null hypothesis is true supplied by the sample

- ❖ Hence, the decision being:
  - a. If *p-value*  $< \alpha$  reject  $H_0$
  - b. If *p-value*  $\geq \alpha$  accept  $H_0$

### Power of a test

- ❖ When  $H_0$  is rejected in a hypothesis test, the probability  $\alpha$  of type I error or the *p-value* are known, both being of a small amount.
- ❖ However when  $H_0$  is accepted it may be true or not, the latter leading to make a type II error with probability  $\beta$ .

$\beta$  is the probability of accepting  $H_0$  when it is false. This is a problem because the parameter is unknown, then  $\beta$  is not unique but depending on the infinite values the parameter may take under the alternative hypothesis  $H_1$ :

$$\beta = P(\text{Accept } H_0 / H_0 \text{ false}) = P(\text{Accept } H_0 / H_1 \text{ true})$$

- ❖ Varying the actual value of the parameter in  $H_1$  a function called Operating Characteristic (OC) curve is developed:

$$\beta(\theta) = P(\text{Accept } H_0 / \theta)$$

Nevertheless it is customary to use its complementary, the power function:

$$\text{Power}(\theta) = 1 - \beta(\theta) = P(\text{Reject } H_0 / \theta)$$

- ❖ The power of a test does not directly affect the decision of either accepting or rejecting the null hypothesis, provided that the decision depends only on  $\alpha$  (Newbold P. et al.)
- ❖ However, for a given  $\alpha$ , the power of a test grows when the sample size  $n$  increases

- ❖ By another side, having two tests for a given  $\alpha$  based on two different discrepancies, the test with the smallest  $\beta$  will be preferred. In other words we will prefer the most powerful test (Peña, D.)
- ❖ Finally, as indicated above, to accept  $H_0$  provokes uncertainty because  $\beta$  cannot be calculated and this explains why the test is intended to reject  $H_0$ .

### Confidence Interval Estimation and Hypothesis Testing

- ❖ In general it can be proved that the  $\gamma=1-\alpha$  confidence interval estimation includes all the  $\theta_0$  values of the unknown parameter for which the null hypothesis  $H_0$  would be accepted with a significance level of  $\alpha$
- ❖ As an example let's consider the case of the mean from a  $N(\mu;\sigma)$  with  $\sigma$  unknown:

$$H_0: \mu = \mu_0$$

$$H_1: \mu \neq \mu_0$$

$$\text{If } H_0 \text{ is true} \rightarrow d = \frac{\bar{x} - \mu_0}{s_1/\sqrt{n}} \sim t_{n-1}$$

$$\text{With Acceptance Region } \left| \frac{\bar{x} - \mu_0}{s_1/\sqrt{n}} \right| \leq t_{n-1, \alpha/2}$$

$$\text{and probability } P \left( -t_{n-1, \alpha/2} \leq \frac{\bar{x} - \mu_0}{s_1/\sqrt{n}} \leq +t_{n-1, \alpha/2} \right) = 1 - \alpha$$

$$= \gamma$$

$$\text{Solving for } \mu_0: \mu_0 \in \left[ \bar{x} \mp t_{n-1, \alpha/2} \frac{s_1}{\sqrt{n}} \right]_{\gamma}$$

### 5.3. HYPOTHESIS TESTING FOR ONE POPULATION

#### 5.3.1. Tests for the mean. Normal Populations

Test	Test Statistic $d$	AR	CR	p-value
$H_0: \mu = \mu_0$ $H_1: \mu \neq \mu_0$ $\sigma^2$ known	$\frac{(\bar{x} - \mu_0)\sqrt{n}}{\sigma} \sim Z$	$\frac{ \bar{x} - \mu_0 \sqrt{n}}{\sigma} \leq z_{\alpha/2}$	$\frac{ \bar{x} - \mu_0 \sqrt{n}}{\sigma} > z_{\alpha/2}$	$P( Z  \geq  d_0 ) =$ $= 2 \cdot P(Z \geq  d_0 )$
$H_0: \mu = \mu_0$ $H_1: \mu > \mu_0$ $\sigma^2$ known	idem		$\frac{(\bar{x} - \mu_0)\sqrt{n}}{\sigma} > z_{\alpha}$	$P(Z \geq d_0)$
$H_0: \mu = \mu_0$ $H_1: \mu < \mu_0$ $\sigma^2$ known	idem		$\frac{(\bar{x} - \mu_0)\sqrt{n}}{\sigma} < -z_{\alpha}$	$P(Z \leq d_0)$

$H_0: \mu = \mu_0$ $H_1: \mu \neq \mu_0$ $\sigma^2$ unknown	$\frac{(\bar{x} - \mu_0)\sqrt{n}}{s_1} \sim t_{n-1}$	$\left  \frac{(\bar{x} - \mu_0)\sqrt{n}}{s_1} \right  \leq t_{n-1, \alpha/2}$	$\left  \frac{(\bar{x} - \mu_0)\sqrt{n}}{s_1} \right  > t_{n-1, \alpha/2}$	$P( t_{n-1}  \geq  d_0 ) =$ $= 2 \cdot P(t_{n-1} \geq  d_0 )$
$H_0: \mu = \mu_0$ $H_1: \mu > \mu_0$ $\sigma^2$ unknown	idem		$\frac{(\bar{x} - \mu_0)\sqrt{n}}{s_1} > t_{n-1, \alpha}$	$P(t_{n-1} \geq d_0)$
$H_0: \mu = \mu_0$ $H_1: \mu < \mu_0$ $\sigma^2$ unknown	idem		$\frac{(\bar{x} - \mu_0)\sqrt{n}}{s_1} < -t_{n-1, \alpha}$	$P(t_{n-1} \leq d_0)$

Note 1: Z means a N(0;1)

Note 2: Remember that when n is large enough the Student's t can be approximated by a N(0;1)

Note 3: If the population distribution is unknown but n is large enough the N(0;1) would be used instead of the Student's t in the last three situations

## 5.3.2. Tests for the population proportion (n large enough)

Test	Test Statistic $d$	AR	CR	p-value
$H_0: p = p_0$ $H_1: p \neq p_0$	$\frac{\hat{p} - p_0}{\sqrt{\frac{p_0 q_0}{n}}} \sim Z$	$\frac{ \hat{p} - p_0 }{\sqrt{\frac{p_0 q_0}{n}}} \leq z_{\alpha/2}$	$\frac{ \hat{p} - p_0 }{\sqrt{\frac{p_0 q_0}{n}}} > z_{\alpha/2}$	$P( Z  \geq  d_0 ) =$ $= 2 \cdot P(Z \geq  d_0 )$
$H_0: p = p_0$ $H_1: p > p_0$	idem		$\frac{\hat{p} - p_0}{\sqrt{\frac{p_0 q_0}{n}}} > z_{\alpha}$	$P(Z \geq d_0)$
$H_0: p = p_0$ $H_1: p < p_0$	idem		$\frac{\hat{p} - p_0}{\sqrt{\frac{p_0 q_0}{n}}} < -z_{\alpha}$	$P(Z \leq d_0)$

## 5.3.3. Tests for the variance. Normal Populations.

Test	Test Statistic $d$	AR	CR	p-value
$H_0: \sigma^2 = \sigma_0^2$ $H_1: \sigma^2 \neq \sigma_0^2$	$\frac{(n-1)s_1^2}{\sigma_0^2} \sim \chi_{n-1}^2$	$\chi_{n-1,1-\alpha/2}^2 \leq \frac{(n-1)s_1^2}{\sigma_0^2} \leq \chi_{n-1,\alpha/2}^2$	$\frac{(n-1)s_1^2}{\sigma_0^2} < \chi_{n-1,1-\alpha/2}^2$ $o$ $\frac{(n-1)s_1^2}{\sigma_0^2} > \chi_{n-1,\alpha/2}^2$	$2 \cdot \min[P(\chi_{n-1}^2 \geq d_0), P(\chi_{n-1}^2 \leq d_0)]$
$H_0: \sigma^2 = \sigma_0^2$ $H_1: \sigma^2 > \sigma_0^2$	idem		$\frac{(n-1)s_1^2}{\sigma_0^2} > \chi_{n-1,\alpha}^2$	$P(\chi_{n-1}^2 \geq d_0)$
$H_0: \sigma^2 = \sigma_0^2$ $H_1: \sigma^2 < \sigma_0^2$	idem		$\frac{(n-1)s_1^2}{\sigma_0^2} < \chi_{n-1,1-\alpha}^2$	$P(\chi_{n-1}^2 \leq d_0)$

## 5.4. HYPOTHESIS TESTING FOR TWO POPULATIONS

### 5.4.1. Tests for the differences of population means. Independent Samples. Normal Populations

Test	Test Statistic $d$	AR	CR	p-value
$H_0: \mu_X - \mu_Y = D$ $H_1: \mu_X - \mu_Y \neq D$ $\sigma_X$ and $\sigma_Y$ are known	$\frac{\bar{x} - \bar{y} - D}{\sqrt{\frac{\sigma_x^2}{n} + \frac{\sigma_y^2}{m}}} \sim Z$	$\frac{ \bar{x} - \bar{y} - D }{\sqrt{\frac{\sigma_x^2}{n} + \frac{\sigma_y^2}{m}}} \leq +z_{\alpha/2}$	$\frac{ \bar{x} - \bar{y} - D }{\sqrt{\frac{\sigma_x^2}{n} + \frac{\sigma_y^2}{m}}} > +z_{\alpha/2}$	$P( Z  \geq  d_0 ) =$ $= 2 \cdot P(Z \geq  d_0 )$
$H_0: \mu_X - \mu_Y = D$ $H_1: \mu_X - \mu_Y > D$ $\sigma_X$ and $\sigma_Y$ are known	idem		$\frac{\bar{x} - \bar{y} - D}{\sqrt{\frac{\sigma_x^2}{n} + \frac{\sigma_y^2}{m}}} > z_\alpha$	$P(Z \geq d_0)$
$H_0: \mu_X - \mu_Y = D$ $H_1: \mu_X - \mu_Y < D$ $\sigma_X$ and $\sigma_Y$ are known	idem		$\frac{\bar{x} - \bar{y} - D}{\sqrt{\frac{\sigma_x^2}{n} + \frac{\sigma_y^2}{m}}} < -z_\alpha$	$P(Z \leq d_0)$

Test	Test Statistic $d$	AR	CR	p-value
$H_0: \mu_X - \mu_Y = D$ $H_1: \mu_X - \mu_Y \neq D$ $\sigma_X = \sigma_Y = \sigma$ unknown	$\frac{(\bar{x} - \bar{y}) - D}{s^* \sqrt{\frac{1}{n} + \frac{1}{m}}} \sim t_{n+m-2}$ $s^* = \sqrt{\frac{(n-1)s_{1x}^2 + (m-1)s_{1y}^2}{n+m-2}}$	$ d  \leq t_{n+m-2, \alpha/2}$	$ d  > t_{n+m-2, \alpha/2}$	$P( t_{n+m-2}  \geq  d_0 ) =$ $= 2 \cdot P(t_{n+m-2} \geq  d_0 )$
$H_0: \mu_X - \mu_Y = D$ $H_1: \mu_X - \mu_Y > D$ $\sigma_X = \sigma_Y = \sigma$ unknown	idem		$d > t_{n+m-2, \alpha}$	$P(t_{n+m-2} \geq d_0)$
$H_0: \mu_X - \mu_Y = D$ $H_1: \mu_X - \mu_Y < D$ $\sigma_X = \sigma_Y = \sigma$ unknown	idem		$d < -t_{n+m-2, \alpha}$	$P(t_{n+m-2} \leq d_0)$

Test	Test Statistic $d$	AR	CR	p-value
$H_0: \mu_X - \mu_Y = D$ $H_1: \mu_X - \mu_Y \neq D$ $\sigma_X$ and $\sigma_Y$ unknown n and m large	$\frac{(\bar{x} - \bar{y}) - D}{\sqrt{\frac{s_{1x}^2}{n} + \frac{s_{1y}^2}{m}}} \sim Z$	$ d  \leq +z_{\alpha/2}$	$ d  > +z_{\alpha/2}$	$P( Z  \geq  d_0 ) =$ $= 2 \cdot P(Z \geq  d_0 )$
$H_0: \mu_X - \mu_Y = D$ $H_1: \mu_X - \mu_Y > D$ $\sigma_X$ and $\sigma_Y$ unknown n and m large	idem		$d > z_{\alpha}$	$P(Z \geq d_0)$
$H_0: \mu_X - \mu_Y = D$ $H_1: \mu_X - \mu_Y < D$ $\sigma_X$ and $\sigma_Y$ unknown n and m large	idem		$d < -z_{\alpha}$	$P(Z \leq d_0)$

$H_0: \mu_X - \mu_Y = D$ $H_1: \mu_X - \mu_Y \neq D$ $\sigma_X$ and $\sigma_Y$ unknown $n$ and $m$ small	$\frac{(\bar{x} - \bar{y}) - D}{\sqrt{\frac{s_{1x}^2}{n} + \frac{s_{1y}^2}{m}}} \sim t_k$ $k = n+m-2-g$ $g = \frac{\left[ (m-1) \frac{s_{1x}^2}{n} - (n-1) \frac{s_{1y}^2}{m} \right]^2}{(m-1) \frac{s_{1x}^4}{n^2} - (n-1) \frac{s_{1y}^4}{m^2}}$	$ d  \leq t_{k, \alpha/2}$	$ d  > t_{k, \alpha/2}$	$P( t_k  \geq  d_0 ) =$ $= 2 \cdot P(t_k \geq  d_0 )$
$H_0: \mu_X - \mu_Y = D$ $H_1: \mu_X - \mu_Y > D$ $\sigma_X$ and $\sigma_Y$ unknown $n$ and $m$ small	idem		$d > t_{k, \alpha}$	$P(t_k \geq d_0)$
$H_0: \mu_X - \mu_Y = D$ $H_1: \mu_X - \mu_Y < D$ $\sigma_X$ and $\sigma_Y$ unknown $n$ and $m$ small	idem		$d < -t_{k, \alpha}$	$P(t_k \leq d_0)$

5.4.2. Tests for the difference of population means. Dependent Samples. Normal Populations

Test	Test Statistic $d$	AR	CR	p-value
$H_0: \mu_X - \mu_Y = D$ $H_1: \mu_X - \mu_Y \neq D$	$\frac{(\bar{x} - \bar{y}) - D}{s_{1d} / \sqrt{n}} \sim t_{n-1}$ <p><math>s_{1d}</math> is the bias-corrected sample standard deviation of the differences in the samples</p>	$ d  \leq +t_{n-1, \alpha/2}$	$ d  > +t_{n-1, \alpha/2}$	$P( t_{n-1}  \geq  d_0 ) =$ $= 2 \cdot P(t_{n-1} \geq  d_0 )$
$H_0: \mu_X - \mu_Y = D$ $H_1: \mu_X - \mu_Y > D$	idem		$d > t_{n-1, \alpha}$	$P(t_{n-1} \geq d_0)$
$H_0: \mu_X - \mu_Y = D$ $H_1: \mu_X - \mu_Y < D$	idem		$d < -t_{n-1, \alpha}$	$P(t_{n-1} \leq d_0)$

## 5.4.3. Tests for the difference of proportions. Large independent samples.

Test	Test Statistic $d$	AR	CR	p-value
$H_0: p_X - p_Y = p_0$ $H_1: p_X - p_Y \neq p_0$	$\frac{(\widehat{p}_x - \widehat{p}_y) - p_0}{\sqrt{\frac{\widehat{p}_x \widehat{q}_x}{n} + \frac{\widehat{p}_y \widehat{q}_y}{m}}} \sim Z$	$ d  \leq +z_{\alpha/2}$	$ d  > +z_{\alpha/2}$	$P( Z  \geq  d_0 ) =$ $= 2 \cdot P(Z \geq  d_0 )$
$H_0: p_X - p_Y = p_0$ $H_1: p_X - p_Y > p_0$	idem		$d > z_\alpha$	$P(Z \geq d_0)$
$H_0: p_X - p_Y = p_0$ $H_1: p_X - p_Y < p_0$	idem		$d < -z_\alpha$	$P(Z \leq d_0)$

## 5.4.4. Tests for the quotient of variances. Normal Populations. Independent Samples.

Test	Test Statistic $d$	AR	CR	p-value
$H_0: \sigma_X^2 = \sigma_Y^2$ $H_0: \sigma_X^2 \neq \sigma_Y^2$	$\frac{S_{1X}^2}{S_{1Y}^2} \sim F_{n-1, m-1}$	$F_{n-1, m-1, 1-\alpha/2} \leq d \leq F_{n-1, m-1, \alpha/2}$  where  $F_{n-1, m-1, 1-\alpha/2} = \frac{1}{F_{m-1, n-1, \alpha/2}}$	$d > F_{n-1, m-1, \alpha/2}$ or $d < F_{n-1, m-1, 1-\alpha/2}$	$2 \cdot \min[P(F_{n-1, m-1, \alpha/2} \geq d_0), P(F_{n-1, m-1, \alpha/2} \leq d_0)]$
$H_0: \sigma_X^2 = \sigma_Y^2$ $H_0: \sigma_X^2 > \sigma_Y^2$			$d > F_{n-1, m-1, \alpha}$	$P(F_{n-1, m-1, \alpha/2} \geq d_0)$
$H_0: \sigma_X^2 = \sigma_Y^2$ $H_0: \sigma_X^2 < \sigma_Y^2$			$d < F_{n-1, m-1, 1-\alpha}$	$P(F_{n-1, m-1, \alpha/2} \leq d_0)$