

# FORMULARIO DE LA ASIGNATURA

## DISEÑO DE EXPERIMENTOS Y MODELOS DE REGRESIÓN

Cátedra de Estadística      ETSII – UPM

Versión 2022.02

### Tema 1. Análisis de la varianza

1) Comparación de dos tratamientos:

1.a) Modelo:

$$y_{ij} = \mu_i + u_{ij}, \quad \forall i \in [1, I], j \in [1, n_i] \quad u_{ij} \sim N(0, \sigma)$$

$I$ : número de tratamientos

$n_i$ : número de observaciones del tratamiento  $i$ -ésimo

1.b) Comparación de medias:

$$\frac{(\bar{y}_{1\bullet} - \bar{y}_{2\bullet}) - (\mu_1 - \mu_2)}{\hat{s}_R \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \rightarrow t_{n-2} \quad \text{donde} \quad \hat{s}_R^2 = \frac{n_1-1}{n_1+n_2-2} \hat{s}_1^2 + \frac{n_2-1}{n_1+n_2-2} \hat{s}_2^2$$

1.c) Comparación de varianzas:

$$\frac{\hat{s}_1^2}{\sigma_1^2} / \frac{\hat{s}_2^2}{\sigma_2^2} \rightarrow F_{n_1-1, n_2-1}$$

2) Comparación de ' $k$ ' tratamientos:

2.a) Modelo:  $y_{ij} = \mu_i + u_{ij}, \quad u_{ij} \sim N(0, \sigma)$

2.b) Descomposición de variabilidad:

$$VT = \sum_{i=1}^K \sum_{j=1}^{n_i} (y_{ij} - \bar{y}_{\bullet\bullet})^2$$

$$VE = \sum_{i=1}^K n_i (\bar{y}_{i\bullet} - \bar{y}_{\bullet\bullet})^2$$

$$VNE = \sum_{i=1}^K \sum_{j=1}^{n_i} (y_{ij} - \bar{y}_{i\bullet})^2 = \sum_{i=1}^K \sum_{j=1}^{n_i} e_{ij}^2$$

2.c) Tabla Análisis de Varianza:

| Fuentes      | Suma de Cuadrados  | Grados de Libertad | Varianzas                   | F  |
|--------------|--|--------------------|-----------------------------|--|
| Tratamientos | $\sum n_i (\bar{y}_{i\bullet} - \bar{y}_{\bullet\bullet})^2$ | $K - 1$            | $VE/(K - 1)$                | $\frac{\sum n_i (\bar{y}_{i\bullet} - \bar{y}_{\bullet\bullet})^2}{(K - 1) \hat{s}_R^2}$ |
| Residual     | $\sum \sum (y_{ij} - \bar{y}_{i\bullet})^2$                  | $n - K$            | $\hat{s}_R^2 = VNE/(n - K)$ |  |
| Total        | $\sum \sum (y_{ij} - \bar{y}_{\bullet\bullet})^2$            | $n - 1$            |                             |  |

2.d) Intervalos de confianza para medias:

$$\mu_i \in \bar{y}_{i\bullet} \pm t_{\alpha/2} \frac{\hat{s}_R}{\sqrt{n_i}}$$

2.e) Contraste dos a dos para la diferencia de medias:

$$t_{ij} = \frac{\bar{y}_{i\bullet} - \bar{y}_{j\bullet} - (\mu_i - \mu_j)}{\hat{s}_R \sqrt{\frac{1}{n_i} + \frac{1}{n_j}}} \rightarrow t_{n-K}$$

## Tema 2. Diseño de experimentos

### 1) Dos factores con interacción

$$y_{ijk} = \mu + \alpha_i + \beta_j + \alpha\beta_{ij} + u_{ijk} \quad \forall i \in [1, I], j \in [1, J], k \in [1, m]$$

$$u_{ijk} \sim N(0, \sigma^2); \sum_{i=1}^I \alpha_i = 0; \sum_{j=1}^J \beta_j = 0; \sum_{i=1}^I \alpha\beta_{ij} = 0, \forall j; \sum_{j=1}^J \alpha\beta_{ij} = 0, \forall i$$

$I$ : número de niveles factor A     $J$ : número de niveles factor B     $m$ : número de repeticiones

#### 1.a) Descomposición de variabilidad:

$$VT = \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^m (y_{ijk} - \bar{y}_{...})^2$$

$$VNE = \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^m e_{ijk}^2$$

$$e_{ijk} = y_{ijk} - \bar{y}_{ij.}$$

$$VE(A) = mJ \sum_{i=1}^I (\bar{y}_{i..} - \bar{y}_{...})^2 = mJ \sum_{i=1}^I (\hat{\alpha}_i)^2$$

$$VE(B) = mI \sum_{j=1}^J (\bar{y}_{.j.} - \bar{y}_{...})^2 = mI \sum_{j=1}^J (\hat{\beta}_j)^2$$

$$VE(A \times B) = m \sum_{i=1}^I \sum_{j=1}^J (\hat{\alpha}\hat{\beta}_{ij})^2$$

#### 1.b) Tabla de Análisis de Varianza:

| Fuentes Variabilidad | Suma de Cuadrados   | Grados de Libertad. | Varianza                                 | F                              | p - valor |
|----------------------|---|---------------------|--|--------------------------------|-----------|
| A                    | $mJ(\bar{y}_{i..} - \bar{y}_{...})^2$   | $I - 1$             | $\hat{s}_A^2 = VE(A)/(I - 1)$            | $\hat{s}_A^2 / \hat{s}_R^2$    | $p_A$     |
| B                    | $mI(\bar{y}_{.j.} - \bar{y}_{...})^2$   | $J - 1$             | $\hat{s}_B^2 = VE(B)/(J - 1)$            | $\hat{s}_B^2 / \hat{s}_R^2$    | $p_B$     |
| $A \times B$         | $m \sum_{i=1}^I \sum_{j=1}^J (\bar{y}_{ij.} - \bar{y}_{i..} - \bar{y}_{.j.} + \bar{y}_{...})^2$ | $(I - 1)(J - 1)$    | $\hat{s}_{AB}^2 = VE(AB)/(I - 1)(J - 1)$ | $\hat{s}_{AB}^2 / \hat{s}_R^2$ | $p_{AB}$  |
| Residual             | $\sum \sum e_{ijk}^2$   | $IJ(m - 1)$         | $\hat{s}_R^2 = VNE/(IJ(m - 1))$          |                                |           |
| Total                | $\sum \sum (y_{ijk} - \bar{y}_{...})^2$   | $n - 1$             |  |                                |           |

#### 1.c) Comparaciones múltiples (interacción nula): factor A

$$(\bar{y}_{i..} - \bar{y}_{j..} - (\alpha_i - \alpha_j)) / \hat{s}_R \sqrt{2/mJ} \rightarrow t_{IJ(m-1)}$$

#### 1.d) Intervalos de confianza (interacción nula): factor A

$$\mu + \alpha_i \in \bar{y}_{i..} \pm t_{\alpha/2} \cdot \hat{s}_R / \sqrt{mJ}$$

#### 1.e) Intervalos de confianza (interacción significativa):

$$\mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} \in \bar{y}_{ij.} \pm t_{\alpha/2} \cdot \hat{s}_R / \sqrt{m}$$

### 2) Bloques aleatorizados

$$y_{ij} = \mu + \alpha_i + \beta_j + u_{ij} \quad \forall i \in [1, I], j \in [1, J]; \quad u_{ijk} \sim N(0, \sigma^2); \sum_{i=1}^I \alpha_i = 0; \sum_{j=1}^J \beta_j = 0$$

$I$ : número de niveles Factor     $J$ : número de niveles Bloque

#### 2.a) Descomposición de variabilidad:

$$VT = \sum_{i=1}^I \sum_{j=1}^J (y_{ij} - \bar{y}_{..})^2 \quad VE(T) = J \sum_{i=1}^I (\bar{y}_{i..} - \bar{y}_{..})^2$$

$$VNE = \sum_{i=1}^I \sum_{j=1}^J e_{ij}^2 \quad VE(B) = I \sum_{j=1}^J (\bar{y}_{.j.} - \bar{y}_{..})^2 \quad e_{ij} = y_{ij} - \bar{y}_{i..} - \bar{y}_{.j.} + \bar{y}_{..}$$

#### 2.b) Tabla de Análisis de Varianza:

| Fuentes Variabilidad | Suma de Cuadrados                                 | Grados de Libertad. | Varianza                           | F                           | p - valor |
|----------------------|---|---------------------|------------------------------------|-----------------------------|-----------|
| Factor               | $J \sum_{i=1}^I (\bar{y}_{i..} - \bar{y}_{..})^2$ | $I - 1$             | $\hat{s}_T^2 = VE(T)/(I - 1)$      | $\hat{s}_T^2 / \hat{s}_R^2$ | $p_T$     |
| Bloque               | $I \sum_{j=1}^J (\bar{y}_{.j.} - \bar{y}_{..})^2$ | $J - 1$             | $\hat{s}_B^2 = VE(B)/(J - 1)$      | $\hat{s}_B^2 / \hat{s}_R^2$ | $p_B$     |
| Residual             | $\sum \sum e_{ij}^2$                              | $(I - 1)(J - 1)$    | $\hat{s}_R^2 = VNE/(I - 1)(J - 1)$ |                             |           |
| Total                | $\sum \sum (y_{ij} - \bar{y}_{..})^2$             | $n - 1$             |                                    |                             |           |

#### 2.c) Intervalo de confianza (para los tratamientos): $\mu + \alpha_i \in \bar{y}_{i..} \pm t_{\alpha/2} \hat{s}_R / \sqrt{J}$

#### 2.d) Contraste dos a dos (para los tratamientos): $(\bar{y}_{i..} - \bar{y}_{j..} - (\alpha_i - \alpha_j)) / \hat{s}_R \sqrt{2/J} \rightarrow t_{(I-1)(J-1)}$

### Tema 3. Modelos de Regresión

1) Regresión lineal simple (RLS)

1.a) Estimación:

$$\hat{\beta}_1 = \text{cov}(x_i, y_i) / \text{var}(x_i) \quad \hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x} \quad \hat{s}_R^2 = \frac{\sum_{i=1}^n e_i^2}{n-2}$$

1.b) Distribución de estimadores:

$$\hat{\beta}_1 \rightarrow N(\beta_1, \sigma^2/(ns_x^2)) \quad \hat{\beta}_0 \rightarrow N\left(\beta_0, \frac{\sigma^2}{n} \left(1 + \frac{\bar{x}^2}{s_x^2}\right)\right) \quad \frac{(n-2)\hat{s}_R^2}{\sigma^2} \rightarrow \chi_{n-2}^2$$

1.c) Contrastos:

$$(\hat{\beta}_1 - \beta_1) / \left( \frac{\hat{s}_R}{\sqrt{n}s_x} \right) \rightarrow t_{n-2} \quad (\hat{\beta}_0 - \beta_0) / \left( \frac{\hat{s}_R}{\sqrt{n}} \sqrt{1 + \frac{\bar{x}^2}{s_x^2}} \right) \rightarrow t_{n-2}$$

1.d) Descomposición de la variabilidad:

$$VE = \hat{\beta}_1^2 n s_x^2 \quad VNE = \hat{s}_R^2 \cdot (n-2) \quad VT = \hat{s}_y^2 \cdot (n-1)$$

2) Regresión lineal múltiple (RLM)

2.a) Estimación:

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{Y} \quad \hat{s}_R^2 = \frac{\sum_{i=1}^n e_i^2}{n-k-1}$$

2.b) Distribución de estimadores:

$$\hat{\boldsymbol{\beta}} \rightarrow N(\boldsymbol{\beta}, \sigma^2 (\mathbf{X}^T \mathbf{X})^{-1}) \quad \frac{(n-k-1)\hat{s}_R^2}{\sigma^2} \rightarrow \chi_{n-k-1}^2$$

2.c) Varianza estimadores para  $k = 2$ :

$$\text{var} \begin{bmatrix} (\hat{\beta}_1) \\ (\hat{\beta}_2) \end{bmatrix} = \begin{pmatrix} \frac{\sigma^2}{ns_1^2(1-r_{12}^2)} & \frac{-r_{12}\sigma^2}{ns_1s_2(1-r_{12}^2)} \\ \frac{-r_{12}\sigma^2}{ns_1s_2(1-r_{12}^2)} & \frac{\sigma^2}{ns_2^2(1-r_{12}^2)} \end{pmatrix}$$

2.d) Contrastos individuales y contraste general:

$$\text{C. Individuales: } \frac{\hat{\beta}_i - \beta_i}{\hat{s}_R \sqrt{q_{ii}}} \rightarrow t_{n-k-1} \quad \text{C. General: } \frac{VE/k}{\hat{s}_R^2} \rightarrow F_{k,n-k-1}$$

2.e) Modelo en diferencias a la media:

$$\hat{\mathbf{b}} = (\tilde{\mathbf{X}}^T \tilde{\mathbf{X}})^{-1} \tilde{\mathbf{X}}^T \tilde{\mathbf{Y}} = (\mathbf{S}_{XX})^{-1} (\mathbf{S}_{XY}) \quad \hat{\mathbf{b}} \rightarrow N(\mathbf{b}, \sigma^2 (\tilde{\mathbf{X}}^T \tilde{\mathbf{X}})^{-1}) = N(\mathbf{b}, \sigma^2 (\mathbf{S}_{XX} \cdot n)^{-1})$$

2.f) Coeficiente de determinación ( $R^2$ ) y coeficiente de determinación corregido ( $\bar{R}^2$ ):

$$R^2 = \frac{VE}{VT} = \frac{\sum(\hat{y}_i - \bar{y})^2}{\sum(y_i - \bar{y})^2} \quad \bar{R}^2 = 1 - \frac{\hat{s}_R^2}{\hat{s}_y^2} = 1 - \frac{VNE}{VT} \cdot \frac{n-1}{n-k-1} = 1 - (1-R^2) \cdot \frac{n-1}{n-k-1}$$

2.g) Cálculo de predicción e intervalo de confianza:

- IC para la media:  $m_h \in \hat{y}_h \pm t_{\frac{\alpha}{2}} \hat{s}_R \sqrt{v_{hh}}$
- IC para una nueva observación:  $y_h \in \hat{y}_h \pm t_{\alpha/2} \hat{s}_R \sqrt{1 + v_{hh}}$

donde  $v_{hh}$  se calcula:

- RLS:  $v_{hh} = \frac{1}{n} \left( 1 + \frac{(x_h - \bar{x})^2}{s_x^2} \right)$
- RLM (alternativa 1):  $v_{hh} = \frac{1}{n} \left( 1 + ((\mathbf{x}_h - \bar{\mathbf{x}})^T \mathbf{S}_{XX}^{-1} (\mathbf{x}_h - \bar{\mathbf{x}})) \right)$  donde  $\mathbf{x}_h = [x_{1,h} \ x_{2,h} \ \dots \ x_{k,h}]^T$
- RLM (alternativa 2):  $v_{hh} = \mathbf{x}_h^T (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{x}_h$  donde  $\mathbf{x}_h = [1 \ x_{1,h} \ x_{2,h} \ \dots \ x_{k,h}]^T$

## 4. Instrucciones Esenciales R

### 0) Previo

```

maquinas = read.table('maquinas.txt', header=T)           # lectura del archivo de texto 'maquinas.txt'
head(maquinas)                                         # Muestra las 6 primeras filas del 'data frame' maquinas
View(maquinas)                                         # Abre una ventana nueva y muestra los datos
names(maquinas)                                         # Proporciona los nombres de las variables del 'data.frame' maquinas
maquinas$maq = factor(maquinas$maq) # Transforma una variable numérica a un *factor*
?head                                              # Con ? delante de una función nos proporciona información de la función

#-----
# Cálculo de probabilidades
dnorm(x, 0, 1)      # Función densidad de una distribución normal N(0,1)
pnorm(q, 0, 1)       # Función distribución de una distribución normal N(0,1)
qnorm(p, 0, 1)       # Función distribución inversa de una distribución normal N(0,1)



|              | F. distr. Inv. | F. distrib. | F. Densidad | Números aleatorios |
|--------------|----------------|-------------|-------------|--------------------|
| Binomial     | pbinom         | qbinom      | dbinom      | rbinom             |
| Chi-Cuadrado | pchisq         | qchisq      | dchisq      | rchisq             |
| Exponencial  | pexp           | qexp        | dexp        | rexp               |
| F            | pf             | qf          | df          | rf                 |
| Geométrica   | pgeom          | qgeom       | dgeom       | rgeom              |
| Normal       | pnorm          | qnorm       | dnorm       | rnorm              |
| Poisson      | ppois          | qpois       | dpois       | rpois              |
| T-Student    | pt             | qt          | dt          | rt                 |


#-----
```

#### Instalación del paquete DisRegETSII:

1. Instalar el paquete “devtools” y cargarlo:
- ```
install.packages("devtools")
library(devtools)
```
2. Instalar el paquete utilizando la función install\_github de devtools
- ```
install_github("javiercara/DisRegETSII")
```

### 1) Comparación de dos tratamientos

```

t.test(rend ~ maq, data = maquinas,
       var.equal=T, conf.level = 0.95) # comparación e intervalo de confianza de dos medias
t.test(maquinas$rend ~ maquinas$maq,
       var.equal=T, conf.level = 0.95) # alternativa a la inst. anterior (válido tmb para var.test, aov)
var.test(rend ~ maq, data = maquinas) # comparación e intervalo de confianza para dos varianzas

```

### 2) Comparación de K tratamientos (modelo con factor)

```

centeno = read.table("centeno.txt", header=TRUE) # Lee el archivo
m = aov(rend ~ sem, data = centeno)           # Análisis de la varianza (aov) de *rend* en función del factor *sem*
anova(m)                                         # Muestra la tabla de análisis de la varianza del modelo *m*
model.tables(m, "means")                         # Proporciona las medias de los distintos tratamientos
tapply(centeno$rend, centeno$sem, mean)          # Otra forma para proporcionar las medias de los distintos tratam.
tapply(centeno$rend, centeno$sem, sd)             # *tapply* es muy útil, puede calcular *sd*, *var*, *length*, etc
residuals(m)                                     # los residuos del modelo (sirve para cualquier modelo)
predict(m)                                         # los valores predichos para cada obs. (sirve para cualquier modelo)
ICplot(m, 'sem', alpha = 0.05)                   # Gráfico de los IC para las medias de cada tratamiento
pairwise.t.test(centeno$rend, centeno$sem,
                p.adjust.method = 'none') # Comparación de medias dos - a - dos

```

### 3) Modelo con dos factores e interacción

```

venenos = read.table("venenos.txt", header=TRUE) # Lee el archivo
m1 = aov(tiempo ~ ant*ven,                      # Realiza el aov de *tiempo* en función de dos factores con interacción
         data = venenos)
m2 = aov(tiempo ~ ant+ven,                      # Realiza el aov de *tiempo* en función de dos factores sin interacción
         data = venenos)
anova(m1)                                         # Tabla de análisis de la varianza del modelo *m1*
model.tables(m1, "means")                         # Proporciona las medias por filas, columnas, tratamientos y la media global
model.tables(m1, "effects")                       # Proporciona las estimaciones de los parámetros del modelo
tapply(venenos$tiempo, venenos$ant, mean)        # medias para cada antídoto (*ant*)
tapply(venenos$tiempo, list(venenos$ant,
                           venenos$ven), mean) # Medias de las combinaciones *ant* y *ven* (tratamientos)
tapply(venenos$tiempo, list(venenos$ant,
                           venenos$ven), var) # Se puede utilizar cualquier función, por ejemplo varianza
ICplot(m1, 'ant', alpha = 0.05) # Gráfico de los IC para las medias de los cuatro *ant*
ICplot(m1, 'ven', alpha = 0.05) # Gráfico de los IC para las medias de los tres *ven*
source("interIC.R")                            # Carga en memoria interIC.R (debe estar en la carpeta)
interIC(m1, 'ant', 'ven', alpha = 0.05) # Gráfico de interacción (IC para las medias de cada tratamiento)

```

## 4) Diagnosis del modelo

```

plot(m1)                      # Realiza los gráficos importantes para la diagnosis
plot(as.numeric(venenos$ven),
     residuals(m1))           # Gráfico de residuos para cada veneno
plot(predict(m1),residuals(m1)) # Gráfico de residuos frente a medias de tratamientos
qqnorm(residuals(m1))          # QQ plot de los residuos para comprobar normalidad
qqline(residuals(m1))          # añade linea al QQ plot de los residuos

```

## 5) Regresión simple

```

cars1 = read.table("cars.txt"), header = T) # carga los datos (el archivo debe estar en La carpeta)
m0 = lm (mpg ~ horse, data = cars1) # estima el modelo de regresión: mpg = b0 + b1 horse + u
summary(m0)                         # proporciona los resultados del modelo m0
plot(cars1$horse,cars1$mpg)         # gráfico de dispersión entre horse (x) y mpg (y)
abline (m0,col="red",wd=2)           # dibuja la recta de reg. estimada en m0 (color rojo y grosor=2)

```

## 6) Regresión múltiple

```

m1 = lm (mpg ~ horse + weight +
          accel, data = cars1)      # estima el modelo de regresión múltiple
m1a = lm (mpg ~ horse +
          I(horse^2) + weight +
          accel, data = cars1)    # incluye el término horse al cuadrado
m1b = lm (mpg ~ horse + weight +
          I(horse*weight) +
          accel, data = cars1)   # incluye el término horse*weight
m1c = lm (log(mpg) ~ horse + weight +
          accel, data = cars1)  # utiliza el log de mpg como variable respuesta

```

## 7) Regresión múltiple con variables cualitativas

```

cars1$origin = factor( cars1$origin,
                       labels = c("USA","EUR","JAP")) # Convierte "origin" a tipo "factor" y se asignan etiquetas
m2 = lm (mpg ~ horse + weight + accel + origin,
          data = cars1)            # modelo con variable cualitativa (utiliza la 1ª como referencia)
cars1$origin = relevel(cars1$origin,
                       ref = "EUR")           # Cambia el nivel de referencia (por defecto el primero)
m2a = lm (mpg ~ horse + weight + accel + origin,
          data = cars1)            # modelo con variable cualitativa con EUR como referencia
m2b = lm (mpg ~ weight + accel + origin + horse*origin,
          data = cars1)            # modelo con parámetros asociados a horse distintos para cada origen
m3 = lm (mpg ~ ., data = cars1) # utiliza todas las variables en cars1 como regresores
anova(m3)                      # análisis de la varianza del modelo m3

```

## 8) Diagnosis del modelo de regresión

```

plot(m0)                      # diagnosis del modelo m0
resi = residuals(m0)          # residuos para las observaciones en cars1
pred = predict(m0)             # valores predichos (ajustados) para las observaciones en cars1
plot(pred,resi)                # Diagnosis: comprueba linealidad y homocedasticidad
qqnorm(resi)                  # Diagnosis: comprueba normalidad
qqline(resi)                  # añade recta al qqplot para comprobar normalidad

```

## 9) Predicción

```

xnueva = data.frame(engine=180,
                     horse =100,weight=3000, accel =10,
                     origin = "JAP", cylinders=4) # coche nuevo para hacer predicción del consumo
predict(m3,xnueva,interval = "confidence") # predicción e intervalo para la media
predict(m3,xnueva,interval = "prediction") # predicción e intervalo para una nueva observación

```

## 10) Otras instrucciones para regresión

```

m4 = step(m3)                  # a partir de m3 selecciona el modelo utilizando STEPWISE
coefficients(m4)               # coeficientes del modelo
confint(m4, level=0.95)        # intervalo de confianza para los coef.
vcov(m4)                       # matriz de varianza de los parámetros estimados
out = influence(m4)            # diagnosis sobre datos atípicos

```

## 5. Tablas

## 1) Distribución Normal Estándar

La tabla muestra los valores  $z$  tales que  $P(Z \leq z)$ .

| $z$ | 0       | 0.01    | 0.02    | 0.03    | 0.04    | 0.05    | 0.06    | 0.07    | 0.08    | 0.09    |
|-----|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| 0.0 | 0.50000 | 0.50399 | 0.50798 | 0.51197 | 0.51595 | 0.51994 | 0.52392 | 0.52790 | 0.53188 | 0.53586 |
| 0.1 | 0.53983 | 0.54380 | 0.54776 | 0.55172 | 0.55567 | 0.55962 | 0.56356 | 0.56749 | 0.57142 | 0.57535 |
| 0.2 | 0.57926 | 0.58317 | 0.58706 | 0.59095 | 0.59483 | 0.59871 | 0.60257 | 0.60642 | 0.61026 | 0.61409 |
| 0.3 | 0.61791 | 0.62172 | 0.62552 | 0.62930 | 0.63307 | 0.63683 | 0.64058 | 0.64431 | 0.64803 | 0.65173 |
| 0.4 | 0.65542 | 0.65910 | 0.66276 | 0.66640 | 0.67003 | 0.67364 | 0.67724 | 0.68082 | 0.68439 | 0.68793 |
| 0.5 | 0.69146 | 0.69497 | 0.69847 | 0.70194 | 0.70540 | 0.70884 | 0.71226 | 0.71566 | 0.71904 | 0.72240 |
| 0.6 | 0.72575 | 0.72907 | 0.73237 | 0.73565 | 0.73891 | 0.74215 | 0.74537 | 0.74857 | 0.75175 | 0.75490 |
| 0.7 | 0.75804 | 0.76115 | 0.76424 | 0.76730 | 0.77035 | 0.77337 | 0.77637 | 0.77935 | 0.78230 | 0.78524 |
| 0.8 | 0.78814 | 0.79103 | 0.79389 | 0.79673 | 0.79955 | 0.80234 | 0.80511 | 0.80785 | 0.81057 | 0.81327 |
| 0.9 | 0.81594 | 0.81859 | 0.82121 | 0.82381 | 0.82639 | 0.82894 | 0.83147 | 0.83398 | 0.83646 | 0.83891 |
| 1.0 | 0.84134 | 0.84375 | 0.84614 | 0.84849 | 0.85083 | 0.85314 | 0.85543 | 0.85769 | 0.85993 | 0.86214 |
| 1.1 | 0.86433 | 0.86650 | 0.86864 | 0.87076 | 0.87286 | 0.87493 | 0.87698 | 0.87900 | 0.88100 | 0.88298 |
| 1.2 | 0.88493 | 0.88686 | 0.88877 | 0.89065 | 0.89251 | 0.89435 | 0.89617 | 0.89796 | 0.89973 | 0.90147 |
| 1.3 | 0.90320 | 0.90490 | 0.90658 | 0.90824 | 0.90988 | 0.91149 | 0.91309 | 0.91466 | 0.91621 | 0.91774 |
| 1.4 | 0.91924 | 0.92073 | 0.92220 | 0.92364 | 0.92507 | 0.92647 | 0.92785 | 0.92922 | 0.93056 | 0.93189 |
| 1.5 | 0.93319 | 0.93448 | 0.93574 | 0.93699 | 0.93822 | 0.93943 | 0.94062 | 0.94179 | 0.94295 | 0.94408 |
| 1.6 | 0.94520 | 0.94630 | 0.94738 | 0.94845 | 0.94950 | 0.95053 | 0.95154 | 0.95254 | 0.95352 | 0.95449 |
| 1.7 | 0.95543 | 0.95637 | 0.95728 | 0.95818 | 0.95907 | 0.95994 | 0.96080 | 0.96164 | 0.96246 | 0.96327 |
| 1.8 | 0.96407 | 0.96485 | 0.96562 | 0.96638 | 0.96712 | 0.96784 | 0.96856 | 0.96926 | 0.96995 | 0.97062 |
| 1.9 | 0.97128 | 0.97193 | 0.97257 | 0.97320 | 0.97381 | 0.97441 | 0.97500 | 0.97558 | 0.97615 | 0.97670 |
| 2.0 | 0.97725 | 0.97778 | 0.97831 | 0.97882 | 0.97932 | 0.97982 | 0.98030 | 0.98077 | 0.98124 | 0.98169 |
| 2.1 | 0.98214 | 0.98257 | 0.98300 | 0.98341 | 0.98382 | 0.98422 | 0.98461 | 0.98500 | 0.98537 | 0.98574 |
| 2.2 | 0.98610 | 0.98645 | 0.98679 | 0.98713 | 0.98745 | 0.98778 | 0.98809 | 0.98840 | 0.98870 | 0.98899 |
| 2.3 | 0.98928 | 0.98956 | 0.98983 | 0.99010 | 0.99036 | 0.99061 | 0.99086 | 0.99111 | 0.99134 | 0.99158 |
| 2.4 | 0.99180 | 0.99202 | 0.99224 | 0.99245 | 0.99266 | 0.99286 | 0.99305 | 0.99324 | 0.99343 | 0.99361 |
| 2.5 | 0.99379 | 0.99396 | 0.99413 | 0.99430 | 0.99446 | 0.99461 | 0.99477 | 0.99492 | 0.99506 | 0.99520 |
| 2.6 | 0.99534 | 0.99547 | 0.99560 | 0.99573 | 0.99585 | 0.99598 | 0.99609 | 0.99621 | 0.99632 | 0.99643 |
| 2.7 | 0.99653 | 0.99664 | 0.99674 | 0.99683 | 0.99693 | 0.99702 | 0.99711 | 0.99720 | 0.99728 | 0.99736 |
| 2.8 | 0.99744 | 0.99752 | 0.99760 | 0.99767 | 0.99774 | 0.99781 | 0.99788 | 0.99795 | 0.99801 | 0.99807 |
| 2.9 | 0.99813 | 0.99819 | 0.99825 | 0.99831 | 0.99836 | 0.99841 | 0.99846 | 0.99851 | 0.99856 | 0.99861 |
| 3.0 | 0.99865 | 0.99869 | 0.99874 | 0.99878 | 0.99882 | 0.99886 | 0.99889 | 0.99893 | 0.99896 | 0.99900 |
| 3.1 | 0.99903 | 0.99906 | 0.99910 | 0.99913 | 0.99916 | 0.99918 | 0.99921 | 0.99924 | 0.99926 | 0.99929 |
| 3.2 | 0.99931 | 0.99934 | 0.99936 | 0.99938 | 0.99940 | 0.99942 | 0.99944 | 0.99946 | 0.99948 | 0.99950 |
| 3.3 | 0.99952 | 0.99953 | 0.99955 | 0.99957 | 0.99958 | 0.99960 | 0.99961 | 0.99962 | 0.99964 | 0.99965 |
| 3.4 | 0.99966 | 0.99968 | 0.99969 | 0.99970 | 0.99971 | 0.99972 | 0.99973 | 0.99974 | 0.99975 | 0.99976 |
| 3.5 | 0.99977 | 0.99978 | 0.99978 | 0.99979 | 0.99980 | 0.99981 | 0.99981 | 0.99982 | 0.99983 | 0.99983 |
| 3.6 | 0.99984 | 0.99985 | 0.99985 | 0.99986 | 0.99986 | 0.99987 | 0.99987 | 0.99988 | 0.99988 | 0.99989 |
| 3.7 | 0.99989 | 0.99990 | 0.99990 | 0.99990 | 0.99991 | 0.99991 | 0.99992 | 0.99992 | 0.99992 | 0.99992 |
| 3.8 | 0.99993 | 0.99993 | 0.99993 | 0.99994 | 0.99994 | 0.99994 | 0.99994 | 0.99995 | 0.99995 | 0.99995 |
| 3.9 | 0.99995 | 0.99995 | 0.99996 | 0.99996 | 0.99996 | 0.99996 | 0.99996 | 0.99996 | 0.99997 | 0.99997 |
| 4.0 | 0.99997 | 0.99997 | 0.99997 | 0.99997 | 0.99997 | 0.99997 | 0.99998 | 0.99998 | 0.99998 | 0.99998 |
| 4.1 | 0.99998 | 0.99998 | 0.99998 | 0.99998 | 0.99998 | 0.99998 | 0.99998 | 0.99999 | 0.99999 | 0.99999 |

Ejemplo:  $P(Z \leq 1.96) = 0.97500$

## 2) Distribución $\chi^2$

La tabla muestra los valores  $x$  tales que  $P(\chi_n^2 \geq x) = \alpha$

|     |         | $\alpha$ |        |        |         |         |         |         |         |  |
|-----|---------|----------|--------|--------|---------|---------|---------|---------|---------|--|
| n   | 0.995   | 0.99     | 0.975  | 0.95   | 0.5     | 0.05    | 0.025   | 0.01    | 0.005   |  |
| 1   | 0.00004 | 0.0002   | 0.001  | 0.004  | 0.455   | 3.841   | 5.024   | 6.635   | 7.879   |  |
| 2   | 0.010   | 0.020    | 0.051  | 0.103  | 1.386   | 5.991   | 7.378   | 9.210   | 10.597  |  |
| 3   | 0.072   | 0.115    | 0.216  | 0.352  | 2.366   | 7.815   | 9.348   | 11.345  | 12.838  |  |
| 4   | 0.207   | 0.297    | 0.484  | 0.711  | 3.357   | 9.488   | 11.143  | 13.277  | 14.860  |  |
| 5   | 0.412   | 0.554    | 0.831  | 1.145  | 4.351   | 11.070  | 12.833  | 15.086  | 16.750  |  |
| 6   | 0.676   | 0.872    | 1.237  | 1.635  | 5.348   | 12.592  | 14.449  | 16.812  | 18.548  |  |
| 7   | 0.989   | 1.239    | 1.690  | 2.167  | 6.346   | 14.067  | 16.013  | 18.475  | 20.278  |  |
| 8   | 1.344   | 1.646    | 2.180  | 2.733  | 7.344   | 15.507  | 17.535  | 20.090  | 21.955  |  |
| 9   | 1.735   | 2.088    | 2.700  | 3.325  | 8.343   | 16.919  | 19.023  | 21.666  | 23.589  |  |
| 10  | 2.156   | 2.558    | 3.247  | 3.940  | 9.342   | 18.307  | 20.483  | 23.209  | 25.188  |  |
| 11  | 2.603   | 3.053    | 3.816  | 4.575  | 10.341  | 19.675  | 21.920  | 24.725  | 26.757  |  |
| 12  | 3.074   | 3.571    | 4.404  | 5.226  | 11.340  | 21.026  | 23.337  | 26.217  | 28.300  |  |
| 13  | 3.565   | 4.107    | 5.009  | 5.892  | 12.340  | 22.362  | 24.736  | 27.688  | 29.819  |  |
| 14  | 4.075   | 4.660    | 5.629  | 6.571  | 13.339  | 23.685  | 26.119  | 29.141  | 31.319  |  |
| 15  | 4.601   | 5.229    | 6.262  | 7.261  | 14.339  | 24.996  | 27.488  | 30.578  | 32.801  |  |
| 16  | 5.142   | 5.812    | 6.908  | 7.962  | 15.338  | 26.296  | 28.845  | 32.000  | 34.267  |  |
| 17  | 5.697   | 6.408    | 7.564  | 8.672  | 16.338  | 27.587  | 30.191  | 33.409  | 35.718  |  |
| 18  | 6.265   | 7.015    | 8.231  | 9.390  | 17.338  | 28.869  | 31.526  | 34.805  | 37.156  |  |
| 19  | 6.844   | 7.633    | 8.907  | 10.117 | 18.338  | 30.144  | 32.852  | 36.191  | 38.582  |  |
| 20  | 7.434   | 8.260    | 9.591  | 10.851 | 19.337  | 31.410  | 34.170  | 37.566  | 39.997  |  |
| 21  | 8.034   | 8.897    | 10.283 | 11.591 | 20.337  | 32.671  | 35.479  | 38.932  | 41.401  |  |
| 22  | 8.643   | 9.542    | 10.982 | 12.338 | 21.337  | 33.924  | 36.781  | 40.289  | 42.796  |  |
| 23  | 9.260   | 10.196   | 11.689 | 13.091 | 22.337  | 35.172  | 38.076  | 41.638  | 44.181  |  |
| 24  | 9.886   | 10.856   | 12.401 | 13.848 | 23.337  | 36.415  | 39.364  | 42.980  | 45.559  |  |
| 25  | 10.520  | 11.524   | 13.120 | 14.611 | 24.337  | 37.652  | 40.646  | 44.314  | 46.928  |  |
| 26  | 11.160  | 12.198   | 13.844 | 15.379 | 25.336  | 38.885  | 41.923  | 45.642  | 48.290  |  |
| 27  | 11.808  | 12.879   | 14.573 | 16.151 | 26.336  | 40.113  | 43.195  | 46.963  | 49.645  |  |
| 28  | 12.461  | 13.565   | 15.308 | 16.928 | 27.336  | 41.337  | 44.461  | 48.278  | 50.993  |  |
| 29  | 13.121  | 14.256   | 16.047 | 17.708 | 28.336  | 42.557  | 45.722  | 49.588  | 52.336  |  |
| 30  | 13.787  | 14.953   | 16.791 | 18.493 | 29.336  | 43.773  | 46.979  | 50.892  | 53.672  |  |
| 40  | 20.707  | 22.164   | 24.433 | 26.509 | 39.335  | 55.758  | 59.342  | 63.691  | 66.766  |  |
| 50  | 27.991  | 29.707   | 32.357 | 34.764 | 49.335  | 67.505  | 71.420  | 76.154  | 79.490  |  |
| 60  | 35.534  | 37.485   | 40.482 | 43.188 | 59.335  | 79.082  | 83.298  | 88.379  | 91.952  |  |
| 70  | 43.275  | 45.442   | 48.758 | 51.739 | 69.334  | 90.531  | 95.023  | 100.425 | 104.215 |  |
| 80  | 51.172  | 53.540   | 57.153 | 60.391 | 79.334  | 101.879 | 106.629 | 112.329 | 116.321 |  |
| 90  | 59.196  | 61.754   | 65.647 | 69.126 | 89.334  | 113.145 | 118.136 | 124.116 | 128.299 |  |
| 100 | 67.328  | 70.065   | 74.222 | 77.929 | 99.334  | 124.342 | 129.561 | 135.807 | 140.169 |  |
| 110 | 75.550  | 78.458   | 82.867 | 86.792 | 109.334 | 135.480 | 140.917 | 147.414 | 151.948 |  |
| 120 | 83.852  | 86.923   | 91.573 | 95.705 | 119.334 | 146.567 | 152.211 | 158.950 | 163.648 |  |

Ejemplo:  $P(\chi_9^2 \geq 19.02) = 0.025$

### 3) Distribución t-Student

La tabla muestra los valores  $x$  tales que  $P(t_n \geq x) = \alpha$ .

| $n$ | 0.2   | 0.15  | 0.1   | 0.05  | 0.025  | 0.01   | 0.005  | 0.0025  | 0.001   | 0.0005  |
|-----|-------|-------|-------|-------|--------|--------|--------|---------|---------|---------|
| 1   | 1.376 | 1.963 | 3.078 | 6.314 | 12.706 | 31.821 | 63.657 | 127.321 | 318.309 | 636.619 |
| 2   | 1.061 | 1.386 | 1.886 | 2.920 | 4.303  | 6.965  | 9.925  | 14.089  | 22.327  | 31.599  |
| 3   | 0.978 | 1.250 | 1.638 | 2.353 | 3.182  | 4.541  | 5.841  | 7.453   | 10.215  | 12.924  |
| 4   | 0.941 | 1.190 | 1.533 | 2.132 | 2.776  | 3.747  | 4.604  | 5.598   | 7.173   | 8.610   |
| 5   | 0.920 | 1.156 | 1.476 | 2.015 | 2.571  | 3.365  | 4.032  | 4.773   | 5.893   | 6.869   |
| 6   | 0.906 | 1.134 | 1.440 | 1.943 | 2.447  | 3.143  | 3.707  | 4.317   | 5.208   | 5.959   |
| 7   | 0.896 | 1.119 | 1.415 | 1.895 | 2.365  | 2.998  | 3.499  | 4.029   | 4.785   | 5.408   |
| 8   | 0.889 | 1.108 | 1.397 | 1.860 | 2.306  | 2.896  | 3.355  | 3.833   | 4.501   | 5.041   |
| 9   | 0.883 | 1.100 | 1.383 | 1.833 | 2.262  | 2.821  | 3.250  | 3.690   | 4.297   | 4.781   |
| 10  | 0.879 | 1.093 | 1.372 | 1.812 | 2.228  | 2.764  | 3.169  | 3.581   | 4.144   | 4.587   |
| 11  | 0.876 | 1.088 | 1.363 | 1.796 | 2.201  | 2.718  | 3.106  | 3.497   | 4.025   | 4.437   |
| 12  | 0.873 | 1.083 | 1.356 | 1.782 | 2.179  | 2.681  | 3.055  | 3.428   | 3.930   | 4.318   |
| 13  | 0.870 | 1.079 | 1.350 | 1.771 | 2.160  | 2.650  | 3.012  | 3.372   | 3.852   | 4.221   |
| 14  | 0.868 | 1.076 | 1.345 | 1.761 | 2.145  | 2.624  | 2.977  | 3.326   | 3.787   | 4.140   |
| 15  | 0.866 | 1.074 | 1.341 | 1.753 | 2.131  | 2.602  | 2.947  | 3.286   | 3.733   | 4.073   |
| 16  | 0.865 | 1.071 | 1.337 | 1.746 | 2.120  | 2.583  | 2.921  | 3.252   | 3.686   | 4.015   |
| 17  | 0.863 | 1.069 | 1.333 | 1.740 | 2.110  | 2.567  | 2.898  | 3.222   | 3.646   | 3.965   |
| 18  | 0.862 | 1.067 | 1.330 | 1.734 | 2.101  | 2.552  | 2.878  | 3.197   | 3.610   | 3.922   |
| 19  | 0.861 | 1.066 | 1.328 | 1.729 | 2.093  | 2.539  | 2.861  | 3.174   | 3.579   | 3.883   |
| 20  | 0.860 | 1.064 | 1.325 | 1.725 | 2.086  | 2.528  | 2.845  | 3.153   | 3.552   | 3.850   |
| 21  | 0.859 | 1.063 | 1.323 | 1.721 | 2.080  | 2.518  | 2.831  | 3.135   | 3.527   | 3.819   |
| 22  | 0.858 | 1.061 | 1.321 | 1.717 | 2.074  | 2.508  | 2.819  | 3.119   | 3.505   | 3.792   |
| 23  | 0.858 | 1.060 | 1.319 | 1.714 | 2.069  | 2.500  | 2.807  | 3.104   | 3.485   | 3.768   |
| 24  | 0.857 | 1.059 | 1.318 | 1.711 | 2.064  | 2.492  | 2.797  | 3.091   | 3.467   | 3.745   |
| 25  | 0.856 | 1.058 | 1.316 | 1.708 | 2.060  | 2.485  | 2.787  | 3.078   | 3.450   | 3.725   |
| 26  | 0.856 | 1.058 | 1.315 | 1.706 | 2.056  | 2.479  | 2.779  | 3.067   | 3.435   | 3.707   |
| 27  | 0.855 | 1.057 | 1.314 | 1.703 | 2.052  | 2.473  | 2.771  | 3.057   | 3.421   | 3.690   |
| 28  | 0.855 | 1.056 | 1.313 | 1.701 | 2.048  | 2.467  | 2.763  | 3.047   | 3.408   | 3.674   |
| 29  | 0.854 | 1.055 | 1.311 | 1.699 | 2.045  | 2.462  | 2.756  | 3.038   | 3.396   | 3.659   |
| 30  | 0.854 | 1.055 | 1.310 | 1.697 | 2.042  | 2.457  | 2.750  | 3.030   | 3.385   | 3.646   |
| 40  | 0.851 | 1.050 | 1.303 | 1.684 | 2.021  | 2.423  | 2.704  | 2.971   | 3.307   | 3.551   |
| 50  | 0.849 | 1.047 | 1.299 | 1.676 | 2.009  | 2.403  | 2.678  | 2.937   | 3.261   | 3.496   |
| 60  | 0.848 | 1.045 | 1.296 | 1.671 | 2.000  | 2.390  | 2.660  | 2.915   | 3.232   | 3.460   |
| 70  | 0.847 | 1.044 | 1.294 | 1.667 | 1.994  | 2.381  | 2.648  | 2.899   | 3.211   | 3.435   |
| 80  | 0.846 | 1.043 | 1.292 | 1.664 | 1.990  | 2.374  | 2.639  | 2.887   | 3.195   | 3.416   |
| 90  | 0.846 | 1.042 | 1.291 | 1.662 | 1.987  | 2.368  | 2.632  | 2.878   | 3.183   | 3.402   |
| 100 | 0.845 | 1.042 | 1.290 | 1.660 | 1.984  | 2.364  | 2.626  | 2.871   | 3.174   | 3.390   |
| Inf | 0.842 | 1.036 | 1.282 | 1.645 | 1.960  | 2.326  | 2.576  | 2.807   | 3.090   | 3.291   |

Ejemplo:  $P(t_9 \geq 2.262) = 0.025$

#### 4) Distribución $F(\alpha = 0.05)$

La tabla muestra los valores  $x$  tales que  $P(F_{m,n} \geq x) = 0.05$ .

*m*

| n   | 1       | 2       | 3       | 4       | 5       | 6       | 7       | 8       | 9       | 10      |
|-----|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| 1   | 161.448 | 199.500 | 215.707 | 224.583 | 230.162 | 233.986 | 236.768 | 238.883 | 240.543 | 241.882 |
| 2   | 18.513  | 19.000  | 19.164  | 19.247  | 19.296  | 19.330  | 19.353  | 19.371  | 19.385  | 19.396  |
| 3   | 10.128  | 9.552   | 9.277   | 9.117   | 9.013   | 8.941   | 8.887   | 8.845   | 8.812   | 8.786   |
| 4   | 7.709   | 6.944   | 6.591   | 6.388   | 6.256   | 6.163   | 6.094   | 6.041   | 5.999   | 5.964   |
| 5   | 6.608   | 5.786   | 5.409   | 5.192   | 5.050   | 4.950   | 4.876   | 4.818   | 4.772   | 4.735   |
| 6   | 5.987   | 5.143   | 4.757   | 4.534   | 4.387   | 4.284   | 4.207   | 4.147   | 4.099   | 4.060   |
| 7   | 5.591   | 4.737   | 4.347   | 4.120   | 3.972   | 3.866   | 3.787   | 3.726   | 3.677   | 3.637   |
| 8   | 5.318   | 4.459   | 4.066   | 3.838   | 3.687   | 3.581   | 3.500   | 3.438   | 3.388   | 3.347   |
| 9   | 5.117   | 4.256   | 3.863   | 3.633   | 3.482   | 3.374   | 3.293   | 3.230   | 3.179   | 3.137   |
| 10  | 4.965   | 4.103   | 3.708   | 3.478   | 3.326   | 3.217   | 3.135   | 3.072   | 3.020   | 2.978   |
| 11  | 4.844   | 3.982   | 3.587   | 3.357   | 3.204   | 3.095   | 3.012   | 2.948   | 2.896   | 2.854   |
| 12  | 4.747   | 3.885   | 3.490   | 3.259   | 3.106   | 2.996   | 2.913   | 2.849   | 2.796   | 2.753   |
| 13  | 4.667   | 3.806   | 3.411   | 3.179   | 3.025   | 2.915   | 2.832   | 2.767   | 2.714   | 2.671   |
| 14  | 4.600   | 3.739   | 3.344   | 3.112   | 2.958   | 2.848   | 2.764   | 2.699   | 2.646   | 2.602   |
| 15  | 4.543   | 3.682   | 3.287   | 3.056   | 2.901   | 2.790   | 2.707   | 2.641   | 2.588   | 2.544   |
| 16  | 4.494   | 3.634   | 3.239   | 3.007   | 2.852   | 2.741   | 2.657   | 2.591   | 2.538   | 2.494   |
| 17  | 4.451   | 3.592   | 3.197   | 2.965   | 2.810   | 2.699   | 2.614   | 2.548   | 2.494   | 2.450   |
| 18  | 4.414   | 3.555   | 3.160   | 2.928   | 2.773   | 2.661   | 2.577   | 2.510   | 2.456   | 2.412   |
| 19  | 4.381   | 3.522   | 3.127   | 2.895   | 2.740   | 2.628   | 2.544   | 2.477   | 2.423   | 2.378   |
| 20  | 4.351   | 3.493   | 3.098   | 2.866   | 2.711   | 2.599   | 2.514   | 2.447   | 2.393   | 2.348   |
| 21  | 4.325   | 3.467   | 3.072   | 2.840   | 2.685   | 2.573   | 2.488   | 2.420   | 2.366   | 2.321   |
| 22  | 4.301   | 3.443   | 3.049   | 2.817   | 2.661   | 2.549   | 2.464   | 2.397   | 2.342   | 2.297   |
| 23  | 4.279   | 3.422   | 3.028   | 2.796   | 2.640   | 2.528   | 2.442   | 2.375   | 2.320   | 2.275   |
| 24  | 4.260   | 3.403   | 3.009   | 2.776   | 2.621   | 2.508   | 2.423   | 2.355   | 2.300   | 2.255   |
| 25  | 4.242   | 3.385   | 2.991   | 2.759   | 2.603   | 2.490   | 2.405   | 2.337   | 2.282   | 2.236   |
| 26  | 4.225   | 3.369   | 2.975   | 2.743   | 2.587   | 2.474   | 2.388   | 2.321   | 2.265   | 2.220   |
| 27  | 4.210   | 3.354   | 2.960   | 2.728   | 2.572   | 2.459   | 2.373   | 2.305   | 2.250   | 2.204   |
| 28  | 4.196   | 3.340   | 2.947   | 2.714   | 2.558   | 2.445   | 2.359   | 2.291   | 2.236   | 2.190   |
| 29  | 4.183   | 3.328   | 2.934   | 2.701   | 2.545   | 2.432   | 2.346   | 2.278   | 2.223   | 2.177   |
| 30  | 4.171   | 3.316   | 2.922   | 2.690   | 2.534   | 2.421   | 2.334   | 2.266   | 2.211   | 2.165   |
| 40  | 4.085   | 3.232   | 2.839   | 2.606   | 2.449   | 2.336   | 2.249   | 2.180   | 2.124   | 2.077   |
| 50  | 4.034   | 3.183   | 2.790   | 2.557   | 2.400   | 2.286   | 2.199   | 2.130   | 2.073   | 2.026   |
| 60  | 4.001   | 3.150   | 2.758   | 2.525   | 2.368   | 2.254   | 2.167   | 2.097   | 2.040   | 1.993   |
| 70  | 3.978   | 3.128   | 2.736   | 2.503   | 2.346   | 2.231   | 2.143   | 2.074   | 2.017   | 1.969   |
| 80  | 3.960   | 3.111   | 2.719   | 2.486   | 2.329   | 2.214   | 2.126   | 2.056   | 1.999   | 1.951   |
| 90  | 3.947   | 3.098   | 2.706   | 2.473   | 2.316   | 2.201   | 2.113   | 2.043   | 1.986   | 1.938   |
| 100 | 3.936   | 3.087   | 2.696   | 2.463   | 2.305   | 2.191   | 2.103   | 2.032   | 1.975   | 1.927   |
| Inf | 3.841   | 2.996   | 2.605   | 2.372   | 2.214   | 2.099   | 2.010   | 1.938   | 1.880   | 1.831   |

Ejm:  $P(F_{7,8} \geq 3,50) = 0,05$

**Distribución  $F(\alpha = 0,05)$  (continuación)**

La tabla muestra los valores  $x$  tales que  $P(F_{m,n} \geq x) = 0,05$ .

*m*

| n   | 12      | 15      | 20      | 24      | 30      | 40      | 60      | 100     | 120     | Inf     |
|-----|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| 1   | 243.906 | 245.950 | 248.013 | 249.052 | 250.095 | 251.143 | 252.196 | 253.041 | 253.253 | 254.314 |
| 2   | 19.413  | 19.429  | 19.446  | 19.454  | 19.462  | 19.471  | 19.479  | 19.486  | 19.487  | 19.496  |
| 3   | 8.745   | 8.703   | 8.660   | 8.639   | 8.617   | 8.594   | 8.572   | 8.554   | 8.549   | 8.526   |
| 4   | 5.912   | 5.858   | 5.803   | 5.774   | 5.746   | 5.717   | 5.688   | 5.664   | 5.658   | 5.628   |
| 5   | 4.678   | 4.619   | 4.558   | 4.527   | 4.496   | 4.464   | 4.431   | 4.405   | 4.398   | 4.365   |
| 6   | 4.000   | 3.938   | 3.874   | 3.841   | 3.808   | 3.774   | 3.740   | 3.712   | 3.705   | 3.669   |
| 7   | 3.575   | 3.511   | 3.445   | 3.410   | 3.376   | 3.340   | 3.304   | 3.275   | 3.267   | 3.230   |
| 8   | 3.284   | 3.218   | 3.150   | 3.115   | 3.079   | 3.043   | 3.005   | 2.975   | 2.967   | 2.928   |
| 9   | 3.073   | 3.006   | 2.936   | 2.900   | 2.864   | 2.826   | 2.787   | 2.756   | 2.748   | 2.707   |
| 10  | 2.913   | 2.845   | 2.774   | 2.737   | 2.700   | 2.661   | 2.621   | 2.588   | 2.580   | 2.538   |
| 11  | 2.788   | 2.719   | 2.646   | 2.609   | 2.570   | 2.531   | 2.490   | 2.457   | 2.448   | 2.404   |
| 12  | 2.687   | 2.617   | 2.544   | 2.505   | 2.466   | 2.426   | 2.384   | 2.350   | 2.341   | 2.296   |
| 13  | 2.604   | 2.533   | 2.459   | 2.420   | 2.380   | 2.339   | 2.297   | 2.261   | 2.252   | 2.206   |
| 14  | 2.534   | 2.463   | 2.388   | 2.349   | 2.308   | 2.266   | 2.223   | 2.187   | 2.178   | 2.131   |
| 15  | 2.475   | 2.403   | 2.328   | 2.288   | 2.247   | 2.204   | 2.160   | 2.123   | 2.114   | 2.066   |
| 16  | 2.425   | 2.352   | 2.276   | 2.235   | 2.194   | 2.151   | 2.106   | 2.068   | 2.059   | 2.010   |
| 17  | 2.381   | 2.308   | 2.230   | 2.190   | 2.148   | 2.104   | 2.058   | 2.020   | 2.011   | 1.960   |
| 18  | 2.342   | 2.269   | 2.191   | 2.150   | 2.107   | 2.063   | 2.017   | 1.978   | 1.968   | 1.917   |
| 19  | 2.308   | 2.234   | 2.155   | 2.114   | 2.071   | 2.026   | 1.980   | 1.940   | 1.930   | 1.878   |
| 20  | 2.278   | 2.203   | 2.124   | 2.082   | 2.039   | 1.994   | 1.946   | 1.907   | 1.896   | 1.843   |
| 21  | 2.250   | 2.176   | 2.096   | 2.054   | 2.010   | 1.965   | 1.916   | 1.876   | 1.866   | 1.812   |
| 22  | 2.226   | 2.151   | 2.071   | 2.028   | 1.984   | 1.938   | 1.889   | 1.849   | 1.838   | 1.783   |
| 23  | 2.204   | 2.128   | 2.048   | 2.005   | 1.961   | 1.914   | 1.865   | 1.823   | 1.813   | 1.757   |
| 24  | 2.183   | 2.108   | 2.027   | 1.984   | 1.939   | 1.892   | 1.842   | 1.800   | 1.790   | 1.733   |
| 25  | 2.165   | 2.089   | 2.007   | 1.964   | 1.919   | 1.872   | 1.822   | 1.779   | 1.768   | 1.711   |
| 26  | 2.148   | 2.072   | 1.990   | 1.946   | 1.901   | 1.853   | 1.803   | 1.760   | 1.749   | 1.691   |
| 27  | 2.132   | 2.056   | 1.974   | 1.930   | 1.884   | 1.836   | 1.785   | 1.742   | 1.731   | 1.672   |
| 28  | 2.118   | 2.041   | 1.959   | 1.915   | 1.869   | 1.820   | 1.769   | 1.725   | 1.714   | 1.654   |
| 29  | 2.104   | 2.027   | 1.945   | 1.901   | 1.854   | 1.806   | 1.754   | 1.710   | 1.698   | 1.638   |
| 30  | 2.092   | 2.015   | 1.932   | 1.887   | 1.841   | 1.792   | 1.740   | 1.695   | 1.683   | 1.622   |
| 40  | 2.003   | 1.924   | 1.839   | 1.793   | 1.744   | 1.693   | 1.637   | 1.589   | 1.577   | 1.509   |
| 50  | 1.952   | 1.871   | 1.784   | 1.737   | 1.687   | 1.634   | 1.576   | 1.525   | 1.511   | 1.438   |
| 60  | 1.917   | 1.836   | 1.748   | 1.700   | 1.649   | 1.594   | 1.534   | 1.481   | 1.467   | 1.389   |
| 70  | 1.893   | 1.812   | 1.722   | 1.674   | 1.622   | 1.566   | 1.505   | 1.450   | 1.435   | 1.353   |
| 80  | 1.875   | 1.793   | 1.703   | 1.654   | 1.602   | 1.545   | 1.482   | 1.426   | 1.411   | 1.325   |
| 90  | 1.861   | 1.779   | 1.688   | 1.639   | 1.586   | 1.528   | 1.465   | 1.407   | 1.391   | 1.302   |
| 100 | 1.850   | 1.768   | 1.676   | 1.627   | 1.573   | 1.515   | 1.450   | 1.392   | 1.376   | 1.283   |
| Inf | 1.752   | 1.666   | 1.571   | 1.517   | 1.459   | 1.394   | 1.318   | 1.243   | 1.221   | 1.000   |

## 5) Distribución $F(\alpha = 0,025)$

La tabla muestra los valores  $x$  tales que  $P(F_{m,n} \geq x) = 0,025$ .

*m*

| n   | 1       | 2       | 3       | 4       | 5       | 6       | 7       | 8       | 9       | 10      |
|-----|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| 1   | 647.789 | 799.500 | 864.163 | 899.583 | 921.848 | 937.111 | 948.217 | 956.656 | 963.285 | 968.627 |
| 2   | 38.506  | 39.000  | 39.165  | 39.248  | 39.298  | 39.331  | 39.355  | 39.373  | 39.387  | 39.398  |
| 3   | 17.443  | 16.044  | 15.439  | 15.101  | 14.885  | 14.735  | 14.624  | 14.540  | 14.473  | 14.419  |
| 4   | 12.218  | 10.649  | 9.979   | 9.605   | 9.364   | 9.197   | 9.074   | 8.980   | 8.905   | 8.844   |
| 5   | 10.007  | 8.434   | 7.764   | 7.388   | 7.146   | 6.978   | 6.853   | 6.757   | 6.681   | 6.619   |
| 6   | 8.813   | 7.260   | 6.599   | 6.227   | 5.988   | 5.820   | 5.695   | 5.600   | 5.523   | 5.461   |
| 7   | 8.073   | 6.542   | 5.890   | 5.523   | 5.285   | 5.119   | 4.995   | 4.899   | 4.823   | 4.761   |
| 8   | 7.571   | 6.059   | 5.416   | 5.053   | 4.817   | 4.652   | 4.529   | 4.433   | 4.357   | 4.295   |
| 9   | 7.209   | 5.715   | 5.078   | 4.718   | 4.484   | 4.320   | 4.197   | 4.102   | 4.026   | 3.964   |
| 10  | 6.937   | 5.456   | 4.826   | 4.468   | 4.236   | 4.072   | 3.950   | 3.855   | 3.779   | 3.717   |
| 11  | 6.724   | 5.256   | 4.630   | 4.275   | 4.044   | 3.881   | 3.759   | 3.664   | 3.588   | 3.526   |
| 12  | 6.554   | 5.096   | 4.474   | 4.121   | 3.891   | 3.728   | 3.607   | 3.512   | 3.436   | 3.374   |
| 13  | 6.414   | 4.965   | 4.347   | 3.996   | 3.767   | 3.604   | 3.483   | 3.388   | 3.312   | 3.250   |
| 14  | 6.298   | 4.857   | 4.242   | 3.892   | 3.663   | 3.501   | 3.380   | 3.285   | 3.209   | 3.147   |
| 15  | 6.200   | 4.765   | 4.153   | 3.804   | 3.576   | 3.415   | 3.293   | 3.199   | 3.123   | 3.060   |
| 16  | 6.115   | 4.687   | 4.077   | 3.729   | 3.502   | 3.341   | 3.219   | 3.125   | 3.049   | 2.986   |
| 17  | 6.042   | 4.619   | 4.011   | 3.665   | 3.438   | 3.277   | 3.156   | 3.061   | 2.985   | 2.922   |
| 18  | 5.978   | 4.560   | 3.954   | 3.608   | 3.382   | 3.221   | 3.100   | 3.005   | 2.929   | 2.866   |
| 19  | 5.922   | 4.508   | 3.903   | 3.559   | 3.333   | 3.172   | 3.051   | 2.956   | 2.880   | 2.817   |
| 20  | 5.871   | 4.461   | 3.859   | 3.515   | 3.289   | 3.128   | 3.007   | 2.913   | 2.837   | 2.774   |
| 21  | 5.827   | 4.420   | 3.819   | 3.475   | 3.250   | 3.090   | 2.969   | 2.874   | 2.798   | 2.735   |
| 22  | 5.786   | 4.383   | 3.783   | 3.440   | 3.215   | 3.055   | 2.934   | 2.839   | 2.763   | 2.700   |
| 23  | 5.750   | 4.349   | 3.750   | 3.408   | 3.183   | 3.023   | 2.902   | 2.808   | 2.731   | 2.668   |
| 24  | 5.717   | 4.319   | 3.721   | 3.379   | 3.155   | 2.995   | 2.874   | 2.779   | 2.703   | 2.640   |
| 25  | 5.686   | 4.291   | 3.694   | 3.353   | 3.129   | 2.969   | 2.848   | 2.753   | 2.677   | 2.613   |
| 26  | 5.659   | 4.265   | 3.670   | 3.329   | 3.105   | 2.945   | 2.824   | 2.729   | 2.653   | 2.590   |
| 27  | 5.633   | 4.242   | 3.647   | 3.307   | 3.083   | 2.923   | 2.802   | 2.707   | 2.631   | 2.568   |
| 28  | 5.610   | 4.221   | 3.626   | 3.286   | 3.063   | 2.903   | 2.782   | 2.687   | 2.611   | 2.547   |
| 29  | 5.588   | 4.201   | 3.607   | 3.267   | 3.044   | 2.884   | 2.763   | 2.669   | 2.592   | 2.529   |
| 30  | 5.568   | 4.182   | 3.589   | 3.250   | 3.026   | 2.867   | 2.746   | 2.651   | 2.575   | 2.511   |
| 40  | 5.424   | 4.051   | 3.463   | 3.126   | 2.904   | 2.744   | 2.624   | 2.529   | 2.452   | 2.388   |
| 50  | 5.340   | 3.975   | 3.390   | 3.054   | 2.833   | 2.674   | 2.553   | 2.458   | 2.381   | 2.317   |
| 60  | 5.286   | 3.925   | 3.343   | 3.008   | 2.786   | 2.627   | 2.507   | 2.412   | 2.334   | 2.270   |
| 70  | 5.247   | 3.890   | 3.309   | 2.975   | 2.754   | 2.595   | 2.474   | 2.379   | 2.302   | 2.237   |
| 80  | 5.218   | 3.864   | 3.284   | 2.950   | 2.730   | 2.571   | 2.450   | 2.355   | 2.277   | 2.213   |
| 90  | 5.196   | 3.844   | 3.265   | 2.932   | 2.711   | 2.552   | 2.432   | 2.336   | 2.259   | 2.194   |
| 100 | 5.179   | 3.828   | 3.250   | 2.917   | 2.696   | 2.537   | 2.417   | 2.321   | 2.244   | 2.179   |
| Inf | 5.024   | 3.689   | 3.116   | 2.786   | 2.567   | 2.408   | 2.288   | 2.192   | 2.114   | 2.048   |

Ejm:  $P(F_{7,8} \geq 4,53) = 0,025$

**Distribución F( $\alpha = 0,025$ ) (continuación)**

La tabla muestra los valores  $x$  tales que  $P(F_{m,n} \geq x) = 0,025$

*m*

| n   | 12      | 15      | 20      | 24      | 30       | 40       | 60       | 100      | 120      | Inf      |
|-----|---------|---------|---------|---------|----------|----------|----------|----------|----------|----------|
| 1   | 976.708 | 984.867 | 993.103 | 997.249 | 1001.414 | 1005.598 | 1009.800 | 1013.175 | 1014.020 | 1018.258 |
| 2   | 39.415  | 39.431  | 39.448  | 39.456  | 39.465   | 39.473   | 39.481   | 39.488   | 39.490   | 39.498   |
| 3   | 14.337  | 14.253  | 14.167  | 14.124  | 14.081   | 14.037   | 13.992   | 13.956   | 13.947   | 13.902   |
| 4   | 8.751   | 8.657   | 8.560   | 8.511   | 8.461    | 8.411    | 8.360    | 8.319    | 8.309    | 8.257    |
| 5   | 6.525   | 6.428   | 6.329   | 6.278   | 6.227    | 6.175    | 6.123    | 6.080    | 6.069    | 6.015    |
| 6   | 5.366   | 5.269   | 5.168   | 5.117   | 5.065    | 5.012    | 4.959    | 4.915    | 4.904    | 4.849    |
| 7   | 4.666   | 4.568   | 4.467   | 4.415   | 4.362    | 4.309    | 4.254    | 4.210    | 4.199    | 4.142    |
| 8   | 4.200   | 4.101   | 3.999   | 3.947   | 3.894    | 3.840    | 3.784    | 3.739    | 3.728    | 3.670    |
| 9   | 3.868   | 3.769   | 3.667   | 3.614   | 3.560    | 3.505    | 3.449    | 3.403    | 3.392    | 3.333    |
| 10  | 3.621   | 3.522   | 3.419   | 3.365   | 3.311    | 3.255    | 3.198    | 3.152    | 3.140    | 3.080    |
| 11  | 3.430   | 3.330   | 3.226   | 3.173   | 3.118    | 3.061    | 3.004    | 2.956    | 2.944    | 2.883    |
| 12  | 3.277   | 3.177   | 3.073   | 3.019   | 2.963    | 2.906    | 2.848    | 2.800    | 2.787    | 2.725    |
| 13  | 3.153   | 3.053   | 2.948   | 2.893   | 2.837    | 2.780    | 2.720    | 2.671    | 2.659    | 2.595    |
| 14  | 3.050   | 2.949   | 2.844   | 2.789   | 2.732    | 2.674    | 2.614    | 2.565    | 2.552    | 2.487    |
| 15  | 2.963   | 2.862   | 2.756   | 2.701   | 2.644    | 2.585    | 2.524    | 2.474    | 2.461    | 2.395    |
| 16  | 2.889   | 2.788   | 2.681   | 2.625   | 2.568    | 2.509    | 2.447    | 2.396    | 2.383    | 2.316    |
| 17  | 2.825   | 2.723   | 2.616   | 2.560   | 2.502    | 2.442    | 2.380    | 2.329    | 2.315    | 2.247    |
| 18  | 2.769   | 2.667   | 2.559   | 2.503   | 2.445    | 2.384    | 2.321    | 2.269    | 2.256    | 2.187    |
| 19  | 2.720   | 2.617   | 2.509   | 2.452   | 2.394    | 2.333    | 2.270    | 2.217    | 2.203    | 2.133    |
| 20  | 2.676   | 2.573   | 2.464   | 2.408   | 2.349    | 2.287    | 2.223    | 2.170    | 2.156    | 2.085    |
| 21  | 2.637   | 2.534   | 2.425   | 2.368   | 2.308    | 2.246    | 2.182    | 2.128    | 2.114    | 2.042    |
| 22  | 2.602   | 2.498   | 2.389   | 2.331   | 2.272    | 2.210    | 2.145    | 2.090    | 2.076    | 2.003    |
| 23  | 2.570   | 2.466   | 2.357   | 2.299   | 2.239    | 2.176    | 2.111    | 2.056    | 2.041    | 1.968    |
| 24  | 2.541   | 2.437   | 2.327   | 2.269   | 2.209    | 2.146    | 2.080    | 2.024    | 2.010    | 1.935    |
| 25  | 2.515   | 2.411   | 2.300   | 2.242   | 2.182    | 2.118    | 2.052    | 1.996    | 1.981    | 1.906    |
| 26  | 2.491   | 2.387   | 2.276   | 2.217   | 2.157    | 2.093    | 2.026    | 1.969    | 1.954    | 1.878    |
| 27  | 2.469   | 2.364   | 2.253   | 2.195   | 2.133    | 2.069    | 2.002    | 1.945    | 1.930    | 1.853    |
| 28  | 2.448   | 2.344   | 2.232   | 2.174   | 2.112    | 2.048    | 1.980    | 1.922    | 1.907    | 1.829    |
| 29  | 2.430   | 2.325   | 2.213   | 2.154   | 2.092    | 2.028    | 1.959    | 1.901    | 1.886    | 1.807    |
| 30  | 2.412   | 2.307   | 2.195   | 2.136   | 2.074    | 2.009    | 1.940    | 1.882    | 1.866    | 1.787    |
| 40  | 2.288   | 2.182   | 2.068   | 2.007   | 1.943    | 1.875    | 1.803    | 1.741    | 1.724    | 1.637    |
| 50  | 2.216   | 2.109   | 1.993   | 1.931   | 1.866    | 1.796    | 1.721    | 1.656    | 1.639    | 1.545    |
| 60  | 2.169   | 2.061   | 1.944   | 1.882   | 1.815    | 1.744    | 1.667    | 1.599    | 1.581    | 1.482    |
| 70  | 2.136   | 2.028   | 1.910   | 1.847   | 1.779    | 1.707    | 1.628    | 1.558    | 1.539    | 1.436    |
| 80  | 2.111   | 2.003   | 1.884   | 1.820   | 1.752    | 1.679    | 1.599    | 1.527    | 1.508    | 1.400    |
| 90  | 2.092   | 1.983   | 1.864   | 1.800   | 1.731    | 1.657    | 1.576    | 1.503    | 1.483    | 1.371    |
| 100 | 2.077   | 1.968   | 1.849   | 1.784   | 1.715    | 1.640    | 1.558    | 1.483    | 1.463    | 1.347    |
| Inf | 1.945   | 1.833   | 1.708   | 1.640   | 1.566    | 1.484    | 1.388    | 1.296    | 1.268    | 1.000    |

## 6) Distribución $F(\alpha = 0,01)$

La tabla muestra los valores  $x$  tales que  $P(F_{m,n} \geq x) = 0,01$

*m*

| n   | 1        | 2        | 3        | 4        | 5        | 6        | 7        | 8        | 9        | 10       |
|-----|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
| 1   | 4052.181 | 4999.500 | 5403.352 | 5624.583 | 5763.650 | 5858.986 | 5928.356 | 5981.070 | 6022.473 | 6055.847 |
| 2   | 98.503   | 99.000   | 99.166   | 99.249   | 99.299   | 99.333   | 99.356   | 99.374   | 99.388   | 99.399   |
| 3   | 34.116   | 30.817   | 29.457   | 28.710   | 28.237   | 27.911   | 27.672   | 27.489   | 27.345   | 27.229   |
| 4   | 21.198   | 18.000   | 16.694   | 15.977   | 15.522   | 15.207   | 14.976   | 14.799   | 14.659   | 14.546   |
| 5   | 16.258   | 13.274   | 12.060   | 11.392   | 10.967   | 10.672   | 10.456   | 10.289   | 10.158   | 10.051   |
| 6   | 13.745   | 10.925   | 9.780    | 9.148    | 8.746    | 8.466    | 8.260    | 8.102    | 7.976    | 7.874    |
| 7   | 12.246   | 9.547    | 8.451    | 7.847    | 7.460    | 7.191    | 6.993    | 6.840    | 6.719    | 6.620    |
| 8   | 11.259   | 8.649    | 7.591    | 7.006    | 6.632    | 6.371    | 6.178    | 6.029    | 5.911    | 5.814    |
| 9   | 10.561   | 8.022    | 6.992    | 6.422    | 6.057    | 5.802    | 5.613    | 5.467    | 5.351    | 5.257    |
| 10  | 10.044   | 7.559    | 6.552    | 5.994    | 5.636    | 5.386    | 5.200    | 5.057    | 4.942    | 4.849    |
| 11  | 9.646    | 7.206    | 6.217    | 5.668    | 5.316    | 5.069    | 4.886    | 4.744    | 4.632    | 4.539    |
| 12  | 9.330    | 6.927    | 5.953    | 5.412    | 5.064    | 4.821    | 4.640    | 4.499    | 4.388    | 4.296    |
| 13  | 9.074    | 6.701    | 5.739    | 5.205    | 4.862    | 4.620    | 4.441    | 4.302    | 4.191    | 4.100    |
| 14  | 8.862    | 6.515    | 5.564    | 5.035    | 4.695    | 4.456    | 4.278    | 4.140    | 4.030    | 3.939    |
| 15  | 8.683    | 6.359    | 5.417    | 4.893    | 4.556    | 4.318    | 4.142    | 4.004    | 3.895    | 3.805    |
| 16  | 8.531    | 6.226    | 5.292    | 4.773    | 4.437    | 4.202    | 4.026    | 3.890    | 3.780    | 3.691    |
| 17  | 8.400    | 6.112    | 5.185    | 4.669    | 4.336    | 4.102    | 3.927    | 3.791    | 3.682    | 3.593    |
| 18  | 8.285    | 6.013    | 5.092    | 4.579    | 4.248    | 4.015    | 3.841    | 3.705    | 3.597    | 3.508    |
| 19  | 8.185    | 5.926    | 5.010    | 4.500    | 4.171    | 3.939    | 3.765    | 3.631    | 3.523    | 3.434    |
| 20  | 8.096    | 5.849    | 4.938    | 4.431    | 4.103    | 3.871    | 3.699    | 3.564    | 3.457    | 3.368    |
| 21  | 8.017    | 5.780    | 4.874    | 4.369    | 4.042    | 3.812    | 3.640    | 3.506    | 3.398    | 3.310    |
| 22  | 7.945    | 5.719    | 4.817    | 4.313    | 3.988    | 3.758    | 3.587    | 3.453    | 3.346    | 3.258    |
| 23  | 7.881    | 5.664    | 4.765    | 4.264    | 3.939    | 3.710    | 3.539    | 3.406    | 3.299    | 3.211    |
| 24  | 7.823    | 5.614    | 4.718    | 4.218    | 3.895    | 3.667    | 3.496    | 3.363    | 3.256    | 3.168    |
| 25  | 7.770    | 5.568    | 4.675    | 4.177    | 3.855    | 3.627    | 3.457    | 3.324    | 3.217    | 3.129    |
| 26  | 7.721    | 5.526    | 4.637    | 4.140    | 3.818    | 3.591    | 3.421    | 3.288    | 3.182    | 3.094    |
| 27  | 7.677    | 5.488    | 4.601    | 4.106    | 3.785    | 3.558    | 3.388    | 3.256    | 3.149    | 3.062    |
| 28  | 7.636    | 5.453    | 4.568    | 4.074    | 3.754    | 3.528    | 3.358    | 3.226    | 3.120    | 3.032    |
| 29  | 7.598    | 5.420    | 4.538    | 4.045    | 3.725    | 3.499    | 3.330    | 3.198    | 3.092    | 3.005    |
| 30  | 7.562    | 5.390    | 4.510    | 4.018    | 3.699    | 3.473    | 3.304    | 3.173    | 3.067    | 2.979    |
| 40  | 7.314    | 5.179    | 4.313    | 3.828    | 3.514    | 3.291    | 3.124    | 2.993    | 2.888    | 2.801    |
| 50  | 7.171    | 5.057    | 4.199    | 3.720    | 3.408    | 3.186    | 3.020    | 2.890    | 2.785    | 2.698    |
| 60  | 7.077    | 4.977    | 4.126    | 3.649    | 3.339    | 3.119    | 2.953    | 2.823    | 2.718    | 2.632    |
| 70  | 7.011    | 4.922    | 4.074    | 3.600    | 3.291    | 3.071    | 2.906    | 2.777    | 2.672    | 2.585    |
| 80  | 6.963    | 4.881    | 4.036    | 3.563    | 3.255    | 3.036    | 2.871    | 2.742    | 2.637    | 2.551    |
| 90  | 6.925    | 4.849    | 4.007    | 3.535    | 3.228    | 3.009    | 2.845    | 2.715    | 2.611    | 2.524    |
| 100 | 6.895    | 4.824    | 3.984    | 3.513    | 3.206    | 2.988    | 2.823    | 2.694    | 2.590    | 2.503    |
| Inf | 6.635    | 4.605    | 3.782    | 3.319    | 3.017    | 2.802    | 2.639    | 2.511    | 2.407    | 2.321    |

Ejemplo:  $P(F_{7,8} \geq 6,18) = 0,01$

**Distribución F( $\alpha = 0,01$ ) (continuación)**

La tabla muestra los valores  $x$  tales que  $P(F_{m,n} \geq x) = 0,01$

*m*

| n   | 12       | 15       | 20       | 24       | 30       | 40       | 60       | 100      | 120      | Inf      |
|-----|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
| 1   | 6106.321 | 6157.285 | 6208.730 | 6234.631 | 6260.649 | 6286.782 | 6313.030 | 6334.110 | 6339.391 | 6365.864 |
| 2   | 99.416   | 99.433   | 99.449   | 99.458   | 99.466   | 99.474   | 99.482   | 99.489   | 99.491   | 99.499   |
| 3   | 27.052   | 26.872   | 26.690   | 26.598   | 26.505   | 26.411   | 26.316   | 26.240   | 26.221   | 26.125   |
| 4   | 14.374   | 14.198   | 14.020   | 13.929   | 13.838   | 13.745   | 13.652   | 13.577   | 13.558   | 13.463   |
| 5   | 9.888    | 9.722    | 9.553    | 9.466    | 9.379    | 9.291    | 9.202    | 9.130    | 9.112    | 9.020    |
| 6   | 7.718    | 7.559    | 7.396    | 7.313    | 7.229    | 7.143    | 7.057    | 6.987    | 6.969    | 6.880    |
| 7   | 6.469    | 6.314    | 6.155    | 6.074    | 5.992    | 5.908    | 5.824    | 5.755    | 5.737    | 5.650    |
| 8   | 5.667    | 5.515    | 5.359    | 5.279    | 5.198    | 5.116    | 5.032    | 4.963    | 4.946    | 4.859    |
| 9   | 5.111    | 4.962    | 4.808    | 4.729    | 4.649    | 4.567    | 4.483    | 4.415    | 4.398    | 4.311    |
| 10  | 4.706    | 4.558    | 4.405    | 4.327    | 4.247    | 4.165    | 4.082    | 4.014    | 3.996    | 3.909    |
| 11  | 4.397    | 4.251    | 4.099    | 4.021    | 3.941    | 3.860    | 3.776    | 3.708    | 3.690    | 3.602    |
| 12  | 4.155    | 4.010    | 3.858    | 3.780    | 3.701    | 3.619    | 3.535    | 3.467    | 3.449    | 3.361    |
| 13  | 3.960    | 3.815    | 3.665    | 3.587    | 3.507    | 3.425    | 3.341    | 3.272    | 3.255    | 3.165    |
| 14  | 3.800    | 3.656    | 3.505    | 3.427    | 3.348    | 3.266    | 3.181    | 3.112    | 3.094    | 3.004    |
| 15  | 3.666    | 3.522    | 3.372    | 3.294    | 3.214    | 3.132    | 3.047    | 2.977    | 2.959    | 2.868    |
| 16  | 3.553    | 3.409    | 3.259    | 3.181    | 3.101    | 3.018    | 2.933    | 2.863    | 2.845    | 2.753    |
| 17  | 3.455    | 3.312    | 3.162    | 3.084    | 3.003    | 2.920    | 2.835    | 2.764    | 2.746    | 2.653    |
| 18  | 3.371    | 3.227    | 3.077    | 2.999    | 2.919    | 2.835    | 2.749    | 2.678    | 2.660    | 2.566    |
| 19  | 3.297    | 3.153    | 3.003    | 2.925    | 2.844    | 2.761    | 2.674    | 2.602    | 2.584    | 2.489    |
| 20  | 3.231    | 3.088    | 2.938    | 2.859    | 2.778    | 2.695    | 2.608    | 2.535    | 2.517    | 2.421    |
| 21  | 3.173    | 3.030    | 2.880    | 2.801    | 2.720    | 2.636    | 2.548    | 2.475    | 2.457    | 2.360    |
| 22  | 3.121    | 2.978    | 2.827    | 2.749    | 2.667    | 2.583    | 2.495    | 2.422    | 2.403    | 2.305    |
| 23  | 3.074    | 2.931    | 2.781    | 2.702    | 2.620    | 2.535    | 2.447    | 2.373    | 2.354    | 2.256    |
| 24  | 3.032    | 2.889    | 2.738    | 2.659    | 2.577    | 2.492    | 2.403    | 2.329    | 2.310    | 2.211    |
| 25  | 2.993    | 2.850    | 2.699    | 2.620    | 2.538    | 2.453    | 2.364    | 2.289    | 2.270    | 2.169    |
| 26  | 2.958    | 2.815    | 2.664    | 2.585    | 2.503    | 2.417    | 2.327    | 2.252    | 2.233    | 2.131    |
| 27  | 2.926    | 2.783    | 2.632    | 2.552    | 2.470    | 2.384    | 2.294    | 2.218    | 2.198    | 2.097    |
| 28  | 2.896    | 2.753    | 2.602    | 2.522    | 2.440    | 2.354    | 2.263    | 2.187    | 2.167    | 2.064    |
| 29  | 2.868    | 2.726    | 2.574    | 2.495    | 2.412    | 2.325    | 2.234    | 2.158    | 2.138    | 2.034    |
| 30  | 2.843    | 2.700    | 2.549    | 2.469    | 2.386    | 2.299    | 2.208    | 2.131    | 2.111    | 2.006    |
| 40  | 2.665    | 2.522    | 2.369    | 2.288    | 2.203    | 2.114    | 2.019    | 1.938    | 1.917    | 1.805    |
| 50  | 2.562    | 2.419    | 2.265    | 2.183    | 2.098    | 2.007    | 1.909    | 1.825    | 1.803    | 1.683    |
| 60  | 2.496    | 2.352    | 2.198    | 2.115    | 2.028    | 1.936    | 1.836    | 1.749    | 1.726    | 1.601    |
| 70  | 2.450    | 2.306    | 2.150    | 2.067    | 1.980    | 1.886    | 1.785    | 1.695    | 1.672    | 1.540    |
| 80  | 2.415    | 2.271    | 2.115    | 2.032    | 1.944    | 1.849    | 1.746    | 1.655    | 1.630    | 1.494    |
| 90  | 2.389    | 2.244    | 2.088    | 2.004    | 1.916    | 1.820    | 1.716    | 1.623    | 1.598    | 1.457    |
| 100 | 2.368    | 2.223    | 2.067    | 1.983    | 1.893    | 1.797    | 1.692    | 1.598    | 1.572    | 1.427    |
| Inf | 2.185    | 2.039    | 1.878    | 1.791    | 1.696    | 1.592    | 1.473    | 1.358    | 1.325    | 1.000    |