

Example

Multicollinearity

Consumption Expenditure in Relation to Income and Wealth

TABLE 10.5
Hypothetical Data
on Consumption
Expenditure Y,
Income X_2 , and
Wealth X_3

Y, \$	X_2 , \$	X_3 , \$
70	80	810
65	100	1009
90	120	1273
95	140	1425
110	160	1633
115	180	1876
120	200	2052
140	220	2201
155	240	2435
150	260	2686

Source	SS	df	MS	Number of obs =
Model	8565.55487	2	4282.77794	10
Residual	324.445926	7	46.349418	F(2, 7) = 92.48
Total	8890	9	987.777778	Prob > F = 0.0000
				R-squared = 0.9635
				Adj R-squared = 0.9531
				Root MSE = 6.888

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
x2	.9415373	.8228983	1.14	0.290	-1.084388 2.887383
x3	-.0424345	.0886845	-0.53	0.615	-.2331757 .1483967
_cons	24.77473	6.7525	3.67	0.008	8.897689 48.74186

$$\hat{Y}_i = 24.7747 + 0.9415X_{2i} - 0.0424X_{3i}$$

(6.7525) (0.8229) (0.0807)

$$t = (3.6690) (1.1442) (-0.5261)$$

$$R^2 = 0.9635 \quad \bar{R}^2 = 0.9531 \quad df = 10 - 3 = 7$$

Regression shows that income and wealth together explain about 96 % of the variation in consumption expenditure, and yet **neither of the slope coefficients is individually statistically significant**. Moreover, not only is the wealth variable statistically insignificant but also it has the wrong sign

TABLE 10.6
ANOVA Table for
the Consumption-
Income-Wealth
Example

Source of Variation	SS	df	MSS
Due to regression	8,565.5541	2	4,282.7770
Due to residual	324.4459	7	46.3494

$$H_0 = \beta_2 = \beta_3 = 0$$

$$F = \frac{4282.7770}{46.3494} = 92.4019$$

Reject the null hypothesis
(92.4019 > Critical F-value)

This example shows dramatically what multicollinearity does. The fact that the F test is significant but the t values of X_2 and X_3 are individually insignificant means that the two variables are so highly correlated that it is impossible to isolate the individual impact of either income and wealth on consumption

$$\hat{X}_{3i} = 7.5454 + 10.1909X_{2i}$$

Source	SS	df	MS	Number of obs =
Model	3427282.73	1	3427282.73	19
Residual	7123.27273	8	890.409991	F(1, 8) = 3849.82
Total	3434326	9	381591.778	Prob > F = 0.0000
				R-squared = 0.9979
				Adj R-squared = 0.9977
				Root MSE = 29.84

	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
x3					
x2	10.19091	.1642623	62.04	0.000	9.81212 10.5697
_cons	7.545455	29.47581	0.26	0.804	-60.42589 75.5188

$$\hat{Y}_i = 24.4545 + 0.5091X_{2i}$$

Source	SS	df	MS	Number of obs =
Model	8552.72727	1	8552.72727	19
Residual	337.272727	8	42.1590909	F(1, 8) = 202.87
Total	8890	9	987.777778	Prob > F = 0.0000
				R-squared = 0.9621
				Adj R-squared = 0.9573
				Root MSE = 6.493

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
x2	.5090909	.0357428	14.24	0.000	.4266678 .591514
_cons	24.45455	6.413817	3.81	0.005	9.664256 39.24483

$$\hat{Y}_i = 24.411 + 0.0498X_{3i}$$

Source	SS	df	MS	Number of obs =
Model	8504.87666	1	8504.87666	19
Residual	385.123344	8	48.1404181	F(1, 8) = 176.67
Total	8890	9	987.777778	Prob > F = 0.0000
				R-squared = 0.9567
				Adj R-squared = 0.9513
				Root MSE = 6.9383

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
x3	.0497638	.093744	13.29	0.000	.0411391 .0583974
_cons	24.41104	6.874997	3.55	0.007	8.559349 40.26274

Regressions show very clearly that in situations of extreme multicollinearity dropping the highly collinear variable will often make the other X variable statistically significant.

This result would suggest that a way out of extreme collinearity is to drop the collinearity variable.