

# 1 Introduction to Multiple Linear Regression

## 1. Stock & Watson 6.1–6.4

6.1 Recall that

$$\bar{R}^2 = 1 - \frac{n-1}{n-k-1}(1-R^2).$$

Thus, the values of  $\bar{R}^2$  are 0.162, 0.180, 0.181 for columns (1)–(3).

6.2 (a) Workers with college degrees earn \$8.31/hour more, on average, than workers with only high school degrees.

(b) Men earn \$3.85/hour more, on average, than women.

6.3 (a) On average, a worker earns \$0.51/hour more for each year he ages.

(b) Sally's earnings prediction is  $1.87 + 8.32 \times 1 - 3.81 \times 1 + 0.51 \times 29 = \$21.17/\text{hour}$ .

Betsy's earnings prediction is  $1.87 + 8.32 \times 1 - 3.81 \times 1 + 0.51 \times 34 = \$23.72/\text{hour}$ .

6.4 (a) Workers in the Northeast earn \$0.18 more per hour than workers in the West, on average, controlling for other variables in the regression. Workers in the Midwest earn \$1.23 less per hour than workers in the West, on average, controlling for other variables in the regression. Workers in the South earn \$0.43 less than workers in the West, controlling for other variables in the regression.

(b) The regressor *West* is omitted to avoid perfect multicollinearity. If *West* is included, then the intercept can be written as a perfect linear function of the four regional regressors.

(c) The expected difference in earnings between Juanita and Jennifer is

$$-0.43 - (-1.23) = \$0.80/\text{hour}$$

## 2. Stock & Watson 6.5

(a) The expected increase in the value of the house is 23,400 dollars (note that *Price* is in 1000 dollars).

(b) The expected increase in the value of the house is  $23,400 + 15,600 = 39,000$  dollars.

(c) The loss in value is 48,800 dollars.

(d)  $R^2 = 1 - \frac{n-k-1}{n-1}(1-\bar{R}^2) = 0.728$

3. Stock & Watson 6.6

- (a) There are other important determinants of a country's crime rate, including demographic characteristics of the population.
- (b) Suppose that the crime rate is positively affected by the fraction of young males in the population, and that counties with high crime rates tend to hire more police. In this case, the size of the police force is likely to be positively correlated with the fraction of young males in the population leading to a positive value for the omitted variable bias, so that  $\hat{\beta}_1 > \beta_1$ .

6. Stock & Watson 6.9

- For omitted variable bias to occur, two conditions must be true:  $X_1$  (the included regressor) is correlated with the omitted variable, and the omitted variable is a determinant of the dependent variable. Since  $X_1$  and  $X_2$  are uncorrelated, the estimator of  $\beta_1$  does not suffer from omitted variable bias.

7. Final, Summer 2014

- (a) Dummy variable trap / perfect multicollinearity
- (b) Exclude either  $F_i$  or  $M_i$ , or drop the constant  $\beta_0$  from the regression equation.

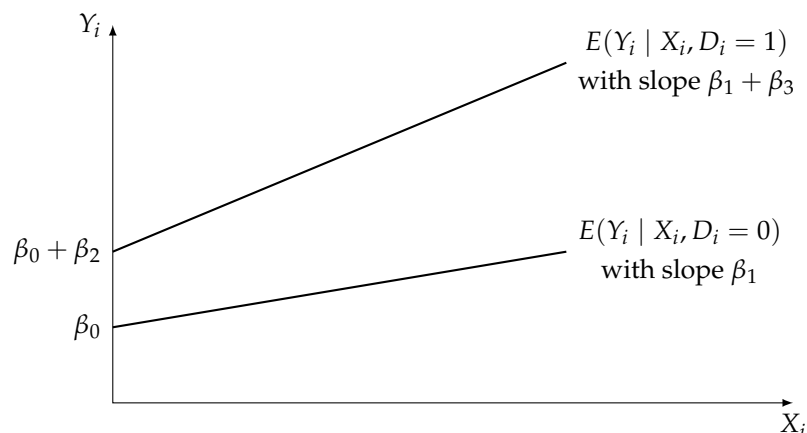
8. Final Q5, Summer 2014

- (a)  $100 + 6 \times 5 = 130$
- (b) 124
- (c) In multiple regression, the  $R^2$  increases whenever a regressor is added, unless the estimated coefficient on the added regressor is exactly zero. To see this, think about starting with one regressor and then adding a second. When you use OLS to estimate the model with both regressors, OLS finds the values of the coefficients that minimize the sum of squared residuals. If OLS happens to choose the coefficient on the new regressor to be exactly zero, then the SSR will be the same whether or not the second variable is included in the regression. But if OLS chooses any value other than zero, then it must be that this value reduced the SSR relative to the regression that excludes this regressor. In practice, it is extremely unusual for an estimated coefficient to be exactly zero, so in general the SSR will decrease when a new regressor is added. But this means that the  $R^2$  generally increases (and never decreases) when a new regressor is added.
- (d) Sampling variability. Even if  $\beta_{ID} = 0$ ,  $\hat{\beta}_{ID} \sim \mathcal{N}(0, \sigma_{\hat{\beta}}^2)$

## 2 Topics in Linear Regression

5. Final Q6, Summer 2014

(a) Assuming  $\beta_0, \beta_1, \beta_2, \beta_3$  are all positive, then



(b) Difference in slopes  $\frac{\partial E(Y_i | X_i, D_i)}{\partial X_i}$  between  $E(Y_i | X_i, D_i = 1)$  and  $E(Y_i | X_i, D_i = 0)$ .

7. Stock & Watson 7.2

(a) The  $t$ -statistic is  $8.31/0.23 = 36.1 > 1.96$ , so the coefficient is statistically significant at the 5% level. The 95% confidence interval is  $8.31 \pm (1.96 \times 0.23)$ .

(b) The  $t$ -statistic is  $-3.85/0.23 = -16.7 > 1.96$ , so the coefficient is statistically significant at the 5% level. The 95% confidence interval is  $-3.85 \pm (1.96 \times 0.23)$ .

9.  $\beta_1$  measures the expected unit change in  $Y_i$  given a one-percent change in  $X_i$ .

10. Stock & Watson 8.7

(a) (i)  $\ln(\text{Earnings})$  for females are, on average, 0.44 lower for men than for women.

(ii) The error term has a standard deviation of 2.65 (measured in log-points).

(iii) Yes. But the regression does not control for many factors (size of firm, industry, profitability, experience and so forth).

(iv) No. In isolation, these results do not imply gender discrimination. Gender discrimination means that two workers, identical in every way but gender, are paid different wages. Thus, it is also important to control for characteristics of the workers that may affect their productivity (education, years of experience, etc.) If these characteristics are systematically different between men and women, then they may

be responsible for the difference in mean wages. (If this were true, it would raise an interesting and important question of why women tend to have less education or less experience than men, but that is a question about something other than gender discrimination.) These are potentially important omitted variables in the regression that will lead to bias in the OLS coefficient estimator for Female.

Since these characteristics were not controlled for in the statistical analysis, it is premature to reach a conclusion about gender discrimination.

- (b) (i) If  $\text{MarketValue}$  increases by 1%, earnings increase by 0.37%.  
(ii) Female is correlated with the two new included variables and at least one of the variables is important for explaining  $\ln(\text{Earnings})$ . Thus the regression in part (a) suffered from omitted variable bias.
- (c) Forgetting about the effect of Return, whose effects seems small and statistically insignificant, the omitted variable bias formula (see equation (6.1)) suggests that Female is negatively correlated with  $\ln(\text{MarketValue})$ .

### 3 Instrumental Variables

#### 1. Stock & Watson 12.5

- (a) Instrument relevance.  $Z_i$  does not enter the population regression for  $X_i$ .
- (b)  $\hat{X}_i$  will be perfectly collinear with  $W_i$ . Alternatively, the first stage regression suffers from perfect multicollinearity.
- (c)  $W_i$  is perfectly multicollinear with the constant term.
- (d)  $Z_i$  violates instrument exogeneity, because it's correlated with the error term.

#### 2. Stock & Watson 12.9

- (a) There are other factors that could affect both the choice to serve in the military and annual earnings. One example could be education, although this could be included in the regression as a control variable. Another variable is "ability" which is difficult to measure, and thus difficult to control for in the regression.
- (b) The draft was determined by a national lottery so the choice of serving in the military was random. Because it was randomly selected, the lottery number is uncorrelated with individual characteristics that may affect earning and hence the instrument is

exogenous. Because it affected the probability of serving in the military, the lottery number is relevant.

### 3. Stock & Watson 12.10

$$\begin{aligned}
 \hat{\beta}_1^{TSLS} &= \frac{s_{ZY}}{s_{ZX}} \\
 &\xrightarrow{p} \frac{cov(Z_i, Y_i)}{cov(Z_i, X_i)} \\
 &= \frac{cov(Z_i, \beta_0 + \beta_1 X_i + \beta_2 W_i + u_i)}{cov(Z_i, X_i)} \\
 &= \frac{\beta_1 cov(Z_i, X_i) + \beta_2 cov(Z_i, W_i)}{cov(Z_i, X_i)}
 \end{aligned}$$

(a) If  $cov(Z_i, W_i) = 0$ ,  $\hat{\beta}_1^{TSLS} \xrightarrow{p} \beta_1$ , the IV estimator is consistent.

(b) If  $cov(Z_i, W_i) \neq 0$ ,  $\hat{\beta}_1^{TSLS} \xrightarrow{p} \frac{\beta_1 cov(Z_i, X_i) + \beta_2 cov(Z_i, W_i)}{cov(Z_i, X_i)}$ , the IV estimator is not consistent.