Appendix F

Answers to Chapter Questions

CHAPTER 2

QUESTION 2.1

When student ability, motivation, age, and other factors in u are not related to attendance, (2.6) would hold. This seems unlikely to be the case.

QUESTION 2.2

About \$9.64. To see this, from the average wages measured in 1976 and 1997 dollars, we can get the CPI deflator as 16.64/5.90 $\approx$ 2.82. When we multiply 3.42 by 2.82, we obtain about 9.64.

QUESTION 2.3

59.26, as can be seen by plugging $shareA = 60$ into equation (2.28). This is not unreasonable: if Candidate A spends 60% of the total money spent, he or she is predicted to receive just over 59% of the vote.

QUESTION 2.4

The equation will be $\widehat{salaryhun} = 9{,}631.91 + 185.01\ roe$, as is easily seen by multiplying equation (2.39) by 10.

QUESTION 2.5

Equation (2.58) can be written as $\mathrm{Var}(\hat{\beta}_0) = (\sigma^2 n^{-1})\left(\sum_{i=1}^{n} x_i^2\right)\Big/\left(\sum_{i=1}^{n}(x_i - \bar{x})^2\right)$, where the term multiplying $\sigma^2 n^{-1}$ is greater than or equal to one, but it is equal to one if and only if $\bar{x} = 0$. In this case, the variance is as small as it can possibly be: $\mathrm{Var}(\hat{\beta}_0) = \sigma^2/n$.

CHAPTER 3

QUESTION 3.1

Just a few factors include age and gender distribution, size of the police force (or, more generally, resources devoted to crime fighting), population, and general historical factors. These factors certainly might be correlated with *prbconv* and *avgsen*, which means (3.5) would not hold. For example, size of the police force is possibly correlated with both *prbcon* and *avgsen*, as some cities put more effort into crime prevention and enforcement. We should try to bring as many of these factors into the equation as possible.

QUESTION 3.2

We use the third property of OLS concerning predicted values and residuals: when we plug the average values of all independent variables into the OLS regression line, we obtain the average value of the dependent variable. So $\overline{colGPA} = 1.29 + .453\,\overline{hsGPA} + .0094\,\overline{ACT} = 1.29 + .453(3.4) + .0094(24.2) \approx 3.06$. You can check the average of *colGPA* in GPA1.RAW to verify this to the second decimal place.

QUESTION 3.3

No. The variable *shareA* is not an exact linear function of *expendA* and *expendB*, even though it is an exact *nonlinear* function: $shareA = 100\cdot[expendA/(expendA + expendB)]$. Therefore, it is legitimate to have *expendA*, *expendB*, and *shareA* as explanatory variables.

QUESTION 3.4

As we discussed in Section 3.4, if we are interested in the effect of x_1 on y, correlation among the other explanatory variables (x_2, x_3, and so on) does not affect $\mathrm{Var}(\hat{\beta}_1)$. These variables are included as controls, and we do not have to worry about this kind of collinearity. Of course, we are controlling for them primarily because we think they are correlated with attendance, but this is necessary to perform a ceteris paribus analysis.

CHAPTER 4

QUESTION 4.1

Under these assumptions, the Gauss-Markov assumptions are satisfied: u is independent of the explanatory variables, so $\mathrm{E}(u|x_1, \ldots, x_k) = \mathrm{E}(u)$, and $\mathrm{Var}(u|x_1, \ldots, x_k) = \mathrm{Var}(u)$. Further, it is easily seen that $\mathrm{E}(u) = 0$. Therefore, MLR.3 and MLR.5 hold. The classical linear model assumptions are not satisfied, because u is not normally distributed (which is a violation of MLR.6).

QUESTION 4.2

H_0: $\beta_1 = 0$, H_1: $\beta_1 < 0$.

QUESTION 4.3

Because $\hat{\beta}_1 = .56 > 0$ and we are testing against H_1: $\beta_1 > 0$, the one-sided p-value is one-half of the two-sided p-value, or .043.

QUESTION 4.4

H_0: $\beta_5 = \beta_6 = \beta_7 = \beta_8 = 0$. $k = 8$ and $q = 4$. The restricted version of the model is

$$score = \beta_0 + \beta_1 classize + \beta_2 expend + \beta_3 tchcomp + \beta_4 enroll + u.$$

QUESTION 4.5

The F statistic for testing exclusion of ACT is $[(.291 - .183)/(1 - .291)](680 - 3) \approx 103.13$. Therefore, the absolute value of the t statistic is about 10.16. The t statistic on ACT is negative, because $\hat{\beta}_{ACT}$ is negative, so $t_{ACT} = -10.16$.

QUESTION 4.6

Not by much. The F test for joint significance of *droprate* and *gradrate* is easily computed from the R-squareds in the table: $F = [(.361 - .353)/(1 - .361)](402/2) \approx 2.52$. The 10% critical value is obtained from Table G.3(a) as 2.30, while the 5% critical value from Table G.3(b) is 3. The p-value is about .082. Thus, *droprate* and *gradrate* are jointly significant at the 10% level, but not at the 5% level. In any case, controlling for these variables has a minor effect on the *b/s* coefficient.

CHAPTER 5

QUESTION 5.1

This requires some assumptions. It seems reasonable to assume that $\beta_2 > 0$ (*score* depends positively on *priGPA*) and Cov(*skipped*,*priGPA*) < 0 (*skipped* and *priGPA* are negatively correlated). This means that $\beta_2\delta_1 < 0$, which means that plim $\tilde{\beta}_1 < \beta_1$. Because β_1 is thought to be negative (or at least nonpositive), a simple regression is likely to overestimate the importance of skipping classes.

QUESTION 5.2

$\hat{\beta}_j \pm 1.96\text{se}(\hat{\beta}_j)$ is the asymptotic 95% confidence interval. Or, we can replace 1.96 with 2.

CHAPTER 6

QUESTION 6.1

Because *fincdol* $= 1{,}000\cdot$*faminc*, the coefficient on *fincdol* will be the coefficient on *faminc* divided by 1,000, or .0927/1,000 = .0000927. The standard error also drops by a factor of 1,000, and so the t statistic does not change, nor do any of the other OLS statistics. For readability, it is better to measure family income in thousands of dollars.

QUESTION 6.2

We can do this generally. The equation is

$$\log(y) = \beta_0 + \beta_1\log(x_1) + \beta_2 x_2 + \ldots,$$

where x_2 is a proportion rather than a percentage. Then, ceteris paribus, $\Delta\log(y) = \beta_2\Delta x_2$, $100\cdot\Delta\log(y) = \beta_2(100\cdot\Delta x_2)$, or $\%\Delta y \approx \beta_2(100\cdot\Delta x_2)$. Now, because Δx_2 is the change in the proportion, $100\cdot\Delta x_2$ is a percentage point change. In particular, if $\Delta x_2 = .01$, then $100\cdot\Delta x_2 = 1$, which corresponds to a one percentage point change. But then β_2 is the percentage change in y when $100\cdot\Delta x_2 = 1$.

QUESTION 6.3

The new model would be $stndfnl = \beta_0 + \beta_1 atndrte + \beta_2 priGPA + \beta_3 ACT + \beta_4 priGPA^2 + \beta_5 ACT^2 + \beta_6 priGPA \cdot atndrte + \beta_7 ACT \cdot atndrte + u$. Therefore, the partial effect of *atndrte* on *stndfnl* is $\beta_1 + \beta_6 priGPA + \beta_7 ACT$. This is what we multiply by $\Delta atndrte$ to obtain the ceteris paribus change in *stndfnl*.

QUESTION 6.4

From equation (6.21), $\bar{R}^2 = 1 - \hat{\sigma}^2/[\text{SST}/(n - 1)]$. For a given sample and a given dependent variable, $\text{SST}/(n - 1)$ is fixed. When we use different sets of explanatory variables, only $\hat{\sigma}^2$ changes. As $\hat{\sigma}^2$ decreases, $\bar{R}^2$ increases. If we make $\hat{\sigma}$, and therefore $\hat{\sigma}^2$, as small as possible, we are making $\bar{R}^2$ as large as possible.

QUESTION 6.5

One possibility is to collect data on annual earnings for a sample of actors, along with profitability of the movies in which they each appeared. In a simple regression analysis, we could relate earnings to profitability. But we should probably control for other factors that may affect salary, such as age, gender, and the kinds of movies in which the actors performed. Methods for including qualitative factors in regression models are considered in Chapter 7.

CHAPTER 7

QUESTION 7.1

No, because it would not be clear when *party* is one and when it is zero. A better name would be something like *Dem*, which is one for Democratic candidates, and zero for Republicans. Or, *Rep*, which is one for Republicans, and zero for Democrats.

QUESTION 7.2

With *outfield* as the base group, we would include the dummy variables *frstbase*, *scndbase*, *thrdbase*, *shrtstop*, and *catcher*.

QUESTION 7.3

The null in this case is H_0: $\delta_1 = \delta_2 = \delta_3 = \delta_4 = 0$, so that there are four restrictions. As usual, we would use an F test (where $q = 4$ and k depends on the number of other explanatory variables).

QUESTION 7.4

Because *tenure* appears as a quadratic, we should allow separate quadratics for men and women. That is, we would add the explanatory variables $female \cdot tenure$ and $female \cdot tenure^2$.

QUESTION 7.5

We plug $pcnv = 0$, $avgsen = 0$, $tottime = 0$, $ptime86 = 0$, $qemp86 = 0$, $black = 1$, and $hispan = 0$ into (7.31): $\widehat{arr86} = .380 - .038(4) + .170 = .398$, or almost .4. It is hard to know whether this is "reasonable." For someone with no prior convictions who was employed throughout the year, this estimate might seem high, but remember that the population consists of men who were already arrested at least once prior to 1986.

CHAPTER 8

QUESTION 8.1

This statement is clearly false. For example, in equation (8.7), the usual standard error for *black* is .147, while the heteroskedasticity-robust standard error is .118.

QUESTION 8.2

The F test would be obtained by regressing $\hat{u}^2$ on *marrmale*, *marrfem*, and *singfem* (*singmale* is the base group). With $n = 526$ and three independent variables in this regression, the *df* are 3 and 522.

QUESTION 8.3

Not really. Because this is a simple regression model, heteroskedasticity only matters if it is related to *inc*. But the Breusch-Pagan test in this case is equivalent to a t statistic in regressing $\hat{u}^2$ on *inc*. A t statistic of .96 is not large enough to reject the homoskedasticity assumption.

QUESTION 8.4

We can use weighted least squares but compute the heteroskedasticity-robust standard errors. In equation (8.26), if our variance model is incorrect, we still have heteroskedasticity. Thus, we can make a guess at the form of heteroskedasticity and perform WLS, but our analysis can be made robust to incorrect forms of heteroskedasticity. Unfortunately, we probably have to explicity obtain the transformed variables.

CHAPTER 9

QUESTION 9.1

These are binary variables, and squaring them has no effect: $black^2 = black$, and $hispan^2 = hispan$.

QUESTION 9.2

When $educ{\cdot}IQ$ is in the equation, the coefficient on *educ*, say β_1, measures the effect of *educ* on log(*wage*) when $IQ = 0$. (The partial effect of education is $\beta_1 + \beta_9 IQ$.) There is no one in the population of interest with an IQ close to zero. At the average population IQ, which is 100, the estimated return to education from column (3) is $.018 + .00034(100) = .052$, which is almost what we obtain as the coefficient on *educ* in column (2).

QUESTION 9.3

No. If *educ** is an integer—which means someone has no education past the previous grade completed—the measurement error is zero. If *educ** is not an integer, *educ* $<$

*educ**, and so the measurement error is negative. At a minimum, e_1 cannot have zero mean, and e_1 and *educ** are probably correlated.

QUESTION 9.4

An incumbent's decision not to run may be systematically related to how he or she expects to do in the election. Therefore, we may only have a sample of incumbents who are stronger, on average, than all possible incumbents who could run. This results in a sample selection problem if the population of interest includes all incumbents. If we are only interested in the effects of campaign expenditures on election outcomes for incumbents who seek reelection, there is no sample selection problem.

CHAPTER 10

QUESTION 10.1

The impact propensity is .48, while the long-run propensity is $.48 - .15 + .32 = .65$.

QUESTION 10.2

The explanatory variables are $x_{t1} = z_t$ and $x_{t2} = z_{t-1}$. The absence of perfect collinearity means that these cannot be constant, and there cannot be an exact linear relationship between them in the sample. This rules out the possibility that all the $z_1, \ldots, z_n$ take on the same value or that the $z_0, z_1, \ldots, z_{n-1}$ take on the same value. But it eliminates other patterns as well. For example, if $z_t = a + bt$ for constants a and b, then $z_{t-1} = a + b(t - 1) = (a + bt) - b = z_t - b$, which is a perfect linear function of z_t.

QUESTION 10.3

If $\{z_t\}$ is slowly moving over time—as is the case for the levels or logs of many economic time series—then z_t and z_{t-1} can be highly correlated. For example, the correlation between $unem_t$ and $unem_{t-1}$ in PHILLIPS.RAW is .74.

QUESTION 10.4

No, because a linear time trend with $\alpha_1 < 0$ becomes more and more negative as t gets large. Since *gfr* cannot be negative, a linear time trend with a negative trend coefficient cannot represent *gfr* in all future time periods.

QUESTION 10.5

The intercept for March is $\beta_0 + \delta_2$. Seasonal dummy variables are strictly exogenous because they follow a deterministic pattern. For example, the months do not change based upon whether either the explanatory variables or the dependent variable change.

CHAPTER 11

QUESTION 11.1

(i) No, because $\mathrm{E}(y_t) = \delta_0 + \delta_1 t$ depends on t. (ii) Yes, because $y_t - \mathrm{E}(y_t) = e_t$ is an i.i.d. sequence.

QUESTION 11.2

We plug $inf_t^e = (1/2)inf_{t-1} + (1/2)inf_{t-2}$ into $inf_t - inf_t^e = \beta_1(unem_t - \mu_0) + e_t$ and rearrange: $inf_t - (1/2)(inf_{t-1} + inf_{t-2}) = \beta_0 + \beta_1 unem_t + e_t$, where $\beta_0 = -\beta_1\mu_0$, as before. Therefore, we would regress y_t on $unem_t$, where $y_t = inf_t - (1/2)(inf_{t-1} + inf_{t-2})$. Note that we lose the first two observations in constructing y_t.

QUESTION 11.3

No, because u_t and u_{t-1} are correlated. In particular, $\text{Cov}(u_t,u_{t-1}) = \text{E}[(e_t + \alpha_1 e_{t-1})(e_{t-1} + \alpha_1 e_{t-2})] = \alpha_1\text{E}(e_{t-1}^2) = \alpha_1\sigma_e^2 \neq 0$ if $\alpha_1 \neq 0$. If the errors are serially correlated, the model cannot be dynamically complete.

CHAPTER 12

QUESTION 12.1

We use equation (12.4). Now, only adjacent terms are correlated. In particular, the covariance between $x_t u_t$ and $x_{t+1}u_{t+1}$ is $x_t x_{t+1}\text{Cov}(u_t,u_{t+1}) = x_t x_{t+1}\alpha\sigma_e^2$. Therefore, the formula is

$$\begin{aligned}\text{Var}(\hat{\beta}_1) &= \text{SST}_x^{-2}\left(\sum_{t=1}^{n} x_t^2\text{Var}(u_t) + 2\sum_{t=1}^{n-1} x_t x_{t+1}\text{E}(u_t u_{t+1})\right)\\ &= \sigma^2/\text{SST}_x + (2/\text{SST}_x^2)\sum_{t=1}^{n-1}\alpha\sigma_e^2 x_t x_{t+1}\\ &= \sigma^2/\text{SST}_x + \alpha\sigma_e^2(2/\text{SST}_x^2)\sum_{t=1}^{n-1} x_t x_{t+1}\end{aligned}$$

where $\sigma^2 = \text{Var}(u_t) = \sigma_e^2 + \alpha_1^2\sigma_e^2 = \sigma_e^2(1 + \alpha_1^2)$. Unless x_t and x_{t+1} are uncorrelated in the sample, the second term is nonzero whenever $\alpha \neq 0$. Notice that if x_t and x_{t+1} are positively correlated and $\alpha < 0$, the true variance is actually *smaller* than the usual variance. When the equation is in levels (as opposed to being differenced), the typical case is $\alpha > 0$, with positive correlation between x_t and x_{t+1}.

QUESTION 12.2

$\hat{\rho} \pm 1.96\text{se}(\hat{\rho})$, where $\text{se}(\hat{\rho})$ is the standard error reported in the regression. Or, we could use the heteroskedasticity-robust standard error. Showing that this is asymptotically valid is complicated because the OLS residuals depend on $\hat{\beta}_j$, but it can be done.

QUESTION 12.3

The model we have in mind is $u_t = \rho_1 u_{t-1} + \rho_4 u_{t-4} + e_t$, and we want to test H_0: $\rho_1 = 0$, $\rho_4 = 0$ against the alternative that H_0 is false. We would run the regression of $\hat{u}_t$ on $\hat{u}_{t-1}$ and $\hat{u}_{t-4}$ to obtain the usual F statistic for joint significance of the two lags. (We are testing two restrictions.)

QUESTION 12.4

We would probably estimate the equation using first differences, as $\hat{\rho} = .92$ is close enough to one to raise questions about the levels regression. See Chapter 18 for more discussion.

QUESTION 12.5

Because there is only one explanatory variable, the White test is easy to compute. Simply regress $\hat{u}_t^2$ on $return_{t-1}$ and $return_{t-1}^2$ (with an intercept, as always) and compute the F test for joint significance of $return_{t-1}$ and $return_{t-1}^2$. If these are jointly significant at a small enough significance level, we reject the null of homoskedasticity.

CHAPTER 13

QUESTION 13.1

Yes, assuming that we have controlled for all relevant factors. The coefficient on *black* is 1.076, and, with a standard error of .174, it is not statistically different from one. The 95% confidence interval is from about .735 to 1.417.

QUESTION 13.2

The coefficient on *highearn* shows that, in the absence of any change in the earnings cap, high earners spend much more time—on the order of 29.2% on average [because $\exp(.256) - 1 \approx .292$]—on workers' compensation.

QUESTION 13.3

First, $\mathrm{E}(v_{i1}) = \mathrm{E}(a_i + u_{i1}) = \mathrm{E}(a_i) + \mathrm{E}(v_{i1}) = 0$. Similarly, $\mathrm{E}(v_{i2}) = 0$. Therefore, the covariance between v_{i1} and v_{i2} is simply $\mathrm{E}(v_{i1}v_{i2}) = \mathrm{E}[(a_i + u_{i1})(a_i + u_{i2})] = \mathrm{E}(a_i^2) + \mathrm{E}(a_iu_{i1}) + \mathrm{E}(a_iu_{i2}) + \mathrm{E}(u_{i1}u_{i2}) = \mathrm{E}(a_i^2)$, because all of the covariance terms are zero by assumption. But $\mathrm{E}(a_i^2) = \mathrm{Var}(a_i)$, because $\mathrm{E}(a_i) = 0$. This causes positive serial correlation across time in the errors within each i, which biases the usual OLS standard errors in a pooled cross-sectional regression.

QUESTION 13.4

Because $\Delta admn = admn_{90} - admn_{85}$ is the difference in binary indicators, it can be -1 if and only if $admn_{90} = 0$ and $admn_{85} = 1$. In other words, Washington state had an administrative per se law in 1985 but it was repealed by 1990.

QUESTION 13.5

No, just as it does not cause bias and inconsistency in a time series regression with strictly exogenous explanatory variables. There are two reasons it is a concern. First, serial correlation in the errors in any equation generally biases the usual OLS standard errors and test statistics. Second, it means that pooled OLS is not as efficient as estimators that account for the serial correlation (as in Chapter 12).

CHAPTER 14

QUESTION 14.1

Whether we use first differencing or the within transformation, we will have trouble estimating the coefficient on $kids_{it}$. For example, using the within transformation, if $kids_{it}$ does not vary for family i, then $\ddot{kids}_{it} = kids_{it} - \overline{kids}_i = 0$ for $t = 1,2,3$. As long as some families have variation in $kids_{it}$, then we can compute the fixed effects estimator, but the kids coefficient could be very imprecisely estimated. This is a form of multicollinearity in fixed effects estimation (or first-differencing estimation).

QUESTION 14.2

If a firm did not receive a grant in the first year, it may or may not receive a grant in the second year. But if a firm did receive a grant in the first year, it could not get a grant in the second year. That is, if $grant_{-1} = 1$, then $grant = 0$. This induces a negative correlation between *grant* and $grant_{-1}$. We can verify this by computing a regression of *grant* on $grant_{-1}$, using the data in JTRAIN.RAW for 1989. Using all firms in the sample, we get

$$\begin{aligned} \widehat{grant} = \underset{(.035)}{.248} - \underset{(.072)}{.248}\ grant_{-1}. \\ n = 157, R^2 = .070. \end{aligned}$$

The coefficient on $grant_{-1}$ must be the negative of the intercept, because $\widehat{grant} = 0$ when $grant_{-1} = 1$.

QUESTION 14.3

It suggests that the unobserved effect a_i is positively correlated with $union_{it}$. Remember, pooled OLS leaves a_i in the error term, while fixed effects removes a_i. By definition, a_i has a positive effect on log(*wage*). By the standard omitted variables analysis (see Chapter 3), OLS has an upward bias when the explanatory variable (*union*) is positively correlated with the omitted variable (a_i). Thus, belonging to a union appears to be positively related to time-constant, unobserved factors that affect wage.

QUESTION 14.4

Not if all sisters within a family have the same mother and father. Then, because the parents' race variables would not change by sister, they would be differenced away in (14.13).

CHAPTER 15

QUESTION 15.1

Probably not. In the simple equation (15.18), years of education is part of the error term. If some men who were assigned low draft lottery numbers obtained additional schooling, then lottery number and education are negatively correlated, which violates the first requirement for an instrumental variable in equation (15.4).

QUESTION 15.2

(i) For (15.27), we require that high school peer group effects carry over to college. Namely, for a given SAT score, a student who went to a high school where smoking marijuana was more popular would smoke more marijuana in college. Even if the identification condition (15.27) holds, the link might be weak.

(ii) We have to assume that percent of students using marijuana at a student's high school is not correlated with unobserved factors that affect college grade point average.

While we are somewhat controlling for high school quality by including *SAT* in the equation, this might not be enough. Perhaps high schools that did a better job of preparing students for college also had fewer students smoking marijuana. Or, marijuana usage could be correlated with average income levels. These are, of course, empirical questions that we may or may not be able to answer.

QUESTION 15.3

While prevalence of the NRA and subscribers to gun magazines are probably correlated with the presence of gun control legislation, it is not obvious that they are uncorrelated with unobserved factors that affect the violent crime rate. In fact, we might argue that a population interested in guns is a reflection of high crime rates, and controlling for economic and demographic variables is not sufficient to capture this. It would be hard to argue persuasively that these are truly exogenous in the violent crime equation.

QUESTION 15.4

As usual, there are two requirements. First, it should be the case that growth in government spending is systematically related to the party of the president, after netting out the investment rate and growth in the labor force. In other words, the instrument must be partially correlated with the endogenous explanatory variable. While we might think that government spending grows more slowly under Republican presidents, this certainly has not always been true in the United States and would have to be tested using the t statistic on REP_{t-1} in the reduced form $gGOV_t = \pi_0 + \pi_1 REP_{t-1} + \pi_2 INVRAT_t + \pi_3 gLAB_t + v_t$. We must assume that the party of the president has no separate effect on *gGDP*. This would be violated if, for example, monetary policy differs systematically by presidential party and has a separate effect on GDP growth.

CHAPTER 16

QUESTION 16.1

Probably not. It is because firms choose price and advertising expenditures jointly that we are not interested in the experiment where, say, advertising changes exogenously and we want to know the effect on price. Instead, we would model price and advertising each as a function of demand and cost variables. This is what falls out of the economic theory.

QUESTION 16.2

We must assume two things. First, money supply growth should appear in equation (16.22), so that it is partially correlated with *inf*. Second, we must assume that money supply growth does not appear in equation (16.23). If we think we must include money supply growth in equation (16.23), then we are still short an instrument for *inf*. Of course, the assumption that money supply growth is exogenous can also be questioned.

QUESTION 16.3

Use the Hausman test from Chapter 15. In particular, let $\hat{v}_2$ be the OLS residuals from the reduced form regression of *open* on log(*pcinc*) and log(*land*). Then, use an OLS regression of *inf* on *open*, log(*pcinc*), and $\hat{v}_2$ and compute the t statistic for significance of $\hat{v}_2$. If $\hat{v}_2$ is significant, the 2SLS and OLS estimates are statistically different.

QUESTION 16.4

The demand equation looks like

$$\log(fish_t) = \beta_0 + \beta_1\log(prcfish_t) + \beta_2\log(inc_t) + \beta_3\log(prcchick_t) + \beta_4\log(prcbeef_t) + u_{t1},$$

where logarithms are used so that all elasticities are constant. By assumption, the demand function contains no seasonality, so the equation does not contain monthly dummy variables (say feb_t, mar_t, …, dec_t, with January as the base month). Also, by assumption, the supply of fish is seasonal, which means that the supply function does depend on at least some of the monthly dummy variables. Even without solving the reduced form for log(*prcfish*), we conclude that it depends on the monthly dummy variables. Since these are exogenous, they can be used as instruments for log(*prcfish*) in the demand equation. Therefore, we can estimate the demand-for-fish equation using monthly dummies as the IVs for log(*prcfish*). Identification requires that at least one monthly dummy variable appears with a nonzero coefficient in the reduced form for log(*prcfish*).

CHAPTER 17

QUESTION 17.1

H_0: $\beta_4 = \beta_5 = \beta_6 = 0$, so that there are three restrictions and therefore three *df* in the *LR* or Wald test.

QUESTION 17.2

We need the partial derivative of $\Phi(\hat{\beta}_0 + \hat{\beta}_1 nwifeinc + \hat{\beta}_2 educ + \hat{\beta}_3 exper + \hat{\beta}_4 exper^2 + \ldots)$ with respect to *exper*, which is $\phi(\cdot)(\hat{\beta}_3 + 2\hat{\beta}_4 exper)$, where $\phi(\cdot)$ is evaluated at the given values and the initial level of experience. Therefore, we need to evaluate the standard normal probability density at $.270 - .012(20.13) + .131(12.3) + .123(10) - .0019(10^2) - .053(42.5) - .868(0) + .036(1) \approx .463$, where we plug in the initial level of experience (10). But $\phi(.463) = (2\pi)^{-1/2}\exp[-(.463^2)/2] \approx .358$. Next, we multiply this by $\hat{\beta}_3 + 2\hat{\beta}_4 exper$, which is evaluated at $exper = 10$. The partial effect using the calculus approximation is $.358[.123 - 2(.0019)(10)] \approx .030$. In other words, at the given values of the explanatory variables and starting at $exper = 10$, the next year of experience increases the probability of labor force participation by about .03.

QUESTION 17.3

No. The number of extramarital affairs is a nonnegative integer, which presumably takes on zero or small numbers for a substantial fraction of the population. It is not realistic to use a Tobit model, which, while allowing a pileup at zero, treats y as being continuously distributed over positive values. Formally, assuming that $y = \max(0,y^*)$, where y^* is normally distributed, is at odds with the discreteness of the number of extramarital affairs when $y > 0$.

QUESTION 17.4

The adjusted standard errors are the usual Poisson MLE standard errors multiplied by $\hat{\sigma} = \sqrt{2} \approx 1.41$, so the adjusted standard errors will be about 41% higher. The quasi-*LR* statistic is the usual *LR* statistic divided by $\hat{\sigma}^2$, so it will be one-half of the usual *LR* statistic.

QUESTION 17.5

By assumption, $mvp_i = \beta_0 + \boldsymbol{x}_i\boldsymbol{\beta} + u_i$, where, as usual, $\boldsymbol{x}_i\boldsymbol{\beta}$ denotes a linear function of the exogenous variables. Now, observed wage is the largest of the minimum wage and the marginal value product, so $wage_i = \max(minwage_i, mvp_i)$, which is very similar to equation (17.34), except that the max operator has replaced the min operator.

CHAPTER 18

QUESTION 18.1

We can plug these values directly into equation (18.1) and take expectations. First, because $z_s = 0$, for all $s < 0$, $y_{-1} = \alpha + u_{-1}$. Then, $z_0 = 1$, so $y_0 = \alpha + \delta_0 + u_0$. For $h \geq 1$, $y_h = \alpha + \delta_{h-1} + \delta_h + u_h$. Because the errors have zero expected values, $\mathrm{E}(y_{-1}) = \alpha$, $\mathrm{E}(y_0) = \alpha + \delta_0$, and $\mathrm{E}(y_h) = \alpha + \delta_{h-1} + \delta_h$, for all $h \geq 1$. As $h \rightarrow \infty$, $\delta_h \rightarrow 0$. It follows that $\mathrm{E}(y_h) \rightarrow \alpha$ as $h \rightarrow \infty$, that is, the expected value of y_h returns to the expected value before the increase in z, at time zero. This makes sense: while the increase in z lasted for two periods, it is still a temporary increase.

QUESTION 18.2

Under the described setup, Δy_t and Δx_t are i.i.d. sequences that are independent of one another. In particular, Δy_t and Δx_t are uncorrelated. If $\hat{\gamma}_1$ is the slope coefficient from regressing Δy_t on Δx_t, $t = 1,2, \ldots, n$, then plim $\hat{\gamma}_1 = 0$. This is as it should be, as we are regressing one I(0) process on another I(0) process, and they are uncorrelated. We write the equation $\Delta y_t = \gamma_0 + \gamma_1 \Delta x_t + e_t$, where $\gamma_0 = \gamma_1 = 0$. Because $\{e_t\}$ is independent of $\{\Delta x_t\}$, the strict exogeneity assumption holds. Moreover, $\{e_t\}$ is serially uncorrelated and homoskedastic. By Theorem 11.2 in Chapter 11, the t statistic for $\hat{\gamma}_1$ has an approximate standard normal distribution. If e_t is normally distributed, the classical linear model assumptions hold, and the t statistic has an exact t distribution.

QUESTION 18.3

Write $x_t = x_{t-1} + a_t$, where $\{a_t\}$ is I(0). By assumption, there is a linear combination, say $s_t = y_t - \beta x_t$, which is I(0). Now, $y_t - \beta x_{t-1} = y_t - \beta(x_t - a_t) = s_t + \beta a_t$. Because s_t and a_t are I(0) by assumption, so is $s_t + \beta a_t$.

QUESTION 18.4

Just use the sum of squared residuals form of the F test and assume homoskedasticity. The restricted SSR is obtained by regressing $\Delta hy6_t - \Delta hy3_{t-1} + (hy6_{t-1} - hy3_{t-2})$ on a constant. Notice that α_0 is the only parameter to estimate in $\Delta hy6_t = \alpha_0 + \gamma_0 \Delta hy3_{t-1} + \delta(hy6_{t-1} - hy3_{t-2})$ when the restrictions are imposed. The unrestricted sum of squared residuals is obtained from equation (18.39).

QUESTION 18.5

We are fitting two equations: $\hat{y}_t = \hat{\alpha} + \hat{\beta}t$ and $\hat{y}_t = \hat{\gamma} + \hat{\delta}year_t$. We can obtain the relationship between the parameters by noting that $year_t = t + 49$. Plugging this into the second equation gives $\hat{y}_t = \hat{\gamma} + \hat{\delta}(t + 49) = (\hat{\gamma} + 49\hat{\delta}) + \hat{\delta}t$. Matching the slope and intercept with the first equation gives $\hat{\delta} = \hat{\beta}$—so that the slopes on t and $year_t$ are identical—and $\hat{\alpha} = \hat{\gamma} + 49\hat{\delta}$. Generally, when we use *year* rather than t, the intercept will change, but the slope will not. (You can verify this by using one of the time series data sets, such as HSEINV.RAW or INVEN.RAW.) Whether we use t or some measure of year does not change fitted values, and, naturally, it does not change forecasts of future values. The intercept simply adjusts appropriately to different ways of including a trend in the regression.