CHAPTER 10

SOLUTIONS TO PROBLEMS

10.1 (i) Disagree. Most time series processes are correlated over time, and many of them strongly correlated. This means they cannot be independent across observations, which simply represent different time periods. Even series that do appear to be roughly uncorrelated – such as stock returns – do not appear to be independently distributed, as you will see in Chapter 12 under dynamic forms of heteroskedasticity.

(ii) Agree. This follows immediately from Theorem 10.1. In particular, we do not need the homoskedasticity and no serial correlation assumptions.

(iii) Disagree. Trending variables are used all the time as dependent variables in a regression model. We do need to be careful in interpreting the results because we may simply find a spurious association between y_t and trending explanatory variables. Including a trend in the regression is a good idea with trending dependent or independent variables. As discussed in Section 10.5, the usual R-squared can be misleading when the dependent variable is trending.

(iv) Agree. With annual data, each time period represents a year and is not associated with any season.

10.3 Write

$$y^* \;=\; \alpha_0 + (\delta_0 + \delta_1 + \delta_2)z^* \;=\; \alpha_0 + LRP \cdot z^*,$$

and take the change: $\Delta y^* \;=\; LRP \cdot \Delta z^*$.

10.5 The functional form was not specified, but a reasonable one is

$$\log(hsestrts_t) \;=\; \alpha_0 + \alpha_1 t + \delta_1 Q2_t + \delta_2 Q3_t + \delta_3 Q3_t + \beta_1 int_t + \beta_2 \log(pcinc_t) + u_t,$$

Where $Q2_t$, $Q3_t$, and $Q4_t$ are quarterly dummy variables (the omitted quarter is the first) and the other variables are self-explanatory. This inclusion of the linear time trend allows the dependent variable and $\log(pcinc_t)$ to trend over time (int_t probably does not contain a trend), and the quarterly dummies allow all variables to display seasonality. The parameter β_2 is an elasticity and $100 \cdot \beta_1$ is a semi-elasticity.

10.7 (i) $pe_{t\text{-}1}$ and $pe_{t\text{-}2}$ must be increasing by the same amount as pe_t.

(ii) The long-run effect, by definition, should be the change in gfr when pe increases permanently. But a permanent increase means the level of pe increases and stays at the new level, and this is achieved by increasing $pe_{t\text{-}2}$, $pe_{t\text{-}1}$, and pe_t by the same amount.

SOLUTIONS TO COMPUTER EXERCISES

C10.1 Let *post79* be a dummy variable equal to one for years after 1979, and zero otherwise. Adding *post79* to equation 10.15) gives

$$\begin{aligned}\widehat{i3}_t &= \underset{(0.43)}{1.30} + \underset{(.076)}{.608}\, inf_t + \underset{(.120)}{.363}\, def_t + \underset{(0.51)}{1.56}\, post79_t \\ n &= 56,\quad R^2 = .664,\quad \bar{R}^2 = .644.\end{aligned}$$

The coefficient on *post79* is statistically significant (t statistic $\approx$ 3.06) and economically large: accounting for inflation and deficits, *i3* was about 1.56 points higher on average in years after 1979. The coefficient on *def* falls once *post79* is included in the regression.

C10.3 Adding log(*prgnp*) to equation (10.38) gives

$$\begin{aligned}\widehat{\log(prepop_t)} &= \underset{(1.26)}{-6.66} - \underset{(.040)}{.212}\log(mincov_t) + \underset{(.222)}{.486}\log(usgnp_t) + \underset{(.080)}{.285}\log(prgnp_t) \\ &\quad - \underset{(.005)}{.027}\, t \\ n &= 38,\quad R^2 = .889,\quad \bar{R}^2 = .876.\end{aligned}$$

The coefficient on log($prgnp_t$) is very statistically significant (t statistic $\approx$ 3.56). Because the dependent and independent variable are in logs, the estimated elasticity of *prepop* with respect to *prgnp* is .285. Including log(*prgnp*) actually increases the size of the minimum wage effect: the estimated elasticity of *prepop* with respect to *mincov* is now –.212, as compared with –.169 in equation (10.38).

C10.5 (i) The coefficient on the time trend in the regression of log(*uclms*) on a linear time trend and 11 monthly dummy variables is about –.0139 (se $\approx$ .0012), which implies that monthly unemployment claims fell by about 1.4% per month on average. The trend is very significant. There is also very strong seasonality in unemployment claims, with 6 of the 11 monthly dummy variables having absolute t statistics above 2. The F statistic for joint significance of the 11 monthly dummies yields p-value $\approx$ .0009.

(ii) When *ez* is added to the regression, its coefficient is about –.508 (se $\approx$ .146). Because this estimate is so large in magnitude, we use equation (7.10): unemployment claims are estimated to fall 100[1 – exp(–.508)] $\approx$ 39.8% after enterprise zone designation.

(iii) We must assume that around the time of *EZ* designation there were not other external factors that caused a shift down in the trend of log(*uclms*). We have controlled for a time trend and seasonality, but this may not be enough.

C10.7 (i) The estimated equation is

$$\widehat{gc}_t = .0081 + .571\, gy_t$$
$$(.0019) \quad (.067)$$
$$n = 36, \quad R^2 = .679.$$

This equation implies that if income growth increases by one percentage point, consumption growth increases by .571 percentage points. The coefficient on gy_t is very statistically significant (t statistic $\approx$ 8.5).

(ii) Adding gy_{t-1} to the equation gives

$$\widehat{gc}_t = .0064 + .552\, gy_t + .096\, gy_{t-1}$$
$$(.0023) \quad (.070) \quad (.069)$$
$$n = 35, \quad R^2 = .695.$$

The t statistic on gy_{t-1} is only about 1.39, so it is not significant at the usual significance levels. (It is significant at the 20% level against a two-sided alternative.) In addition, the coefficient is not especially large. At best there is weak evidence of adjustment lags in consumption.

(iii) If we add $r3_t$ to the model estimated in part (i) we obtain

$$\widehat{gc}_t = .0082 + .578\, gy_t + .00021\, r3_t$$
$$(.0020) \quad (.072) \quad (.00063)$$
$$n = 36, \quad R^2 = .680.$$

The t statistic on $r3_t$ is very small. The estimated coefficient is also practically small: a one-point increase in $r3_t$ reduces consumption growth by about .021 percentage points.

C10.9 (i) The sign of β_2 is fairly clear-cut: as interest rates rise, stock returns fall, so $\beta_2 < 0$. Higher interest rates imply that T-bill and bond investments are more attractive, and also signal a future slowdown in economic activity. The sign of β_1 is less clear. While economic growth can be a good thing for the stock market, it can also signal inflation, which tends to depress stock prices.

(ii) The estimated equation is

$$\widehat{rsp500}_t = 18.84 + .036\, pcip_t - 1.36\, i3_t$$
$$(3.27) \quad (.129) \quad (0.54)$$
$$n = 557, \quad R^2 = .012.$$

A one percentage point increase in industrial production growth is predicted to increase the stock market return by .036 percentage points (a very small effect). On the other hand, a one percentage point increase in interest rates decreases the stock market return by an estimated 1.36 percentage points.

(iii) Only *i3* is statistically significant with *t* statistic ≈ -2.52.

(iv) The regression in part (i) has nothing directly to say about predicting stock returns because the explanatory variables are dated contemporaneously with *rsp500*. In other words, we do not know $i3_t$ before we know $rsp500_t$. What the regression in part (i) says is that a change in *i3* is associated with a contemporaneous change in *rsp500*.

C10.11 (i) The variable *beltlaw* becomes one at $t = 61$, which corresponds to January, 1986. The variable *spdlaw* goes from zero to one at $t = 77$, which corresponds to May, 1987.

(ii) The OLS regression gives

$$\widehat{\log(totacc)} = \underset{(.019)}{10.469} + \underset{(.00016)}{.00275}\, t - \underset{(.0244)}{.0427}\, feb + \underset{(.0244)}{.0798}\, mar + \underset{(.0245)}{.0185}\, apr$$
$$+ \underset{(.0245)}{.0321}\, may + \underset{(.0245)}{.0202}\, jun + \underset{(.0245)}{.0376}\, jul + \underset{(.0245)}{.0540}\, aug$$
$$+ \underset{(.0245)}{.0424}\, sep + \underset{(.0245)}{.0821}\, oct + \underset{(.0245)}{.0713}\, nov + \underset{(.0245)}{.0962}\, dec$$

$n = 108$, $R^2 = .797$

When multiplied by 100, the coefficient on *t* gives roughly the average monthly percentage growth in *totacc*, ignoring seasonal factors. In other words, once seasonality is eliminated, *totacc* grew by about .275% per month over this period, or, 12(.275) = 3.3% at an annual rate.

There is pretty clear evidence of seasonality. Only February has a lower number of total accidents than the base month, January. The peak is in December: roughly, there are 9.6% accidents more in December over January in the average year. The *F* statistic for joint significance of the monthly dummies is $F = 5.15$. With 11 and 95 *df*, this give a *p*-value essentially equal to zero.

(iii) I will report only the coefficients on the new variables:

$$\widehat{\log(totacc)} = \underset{(.063)}{10.640} + \ldots + \underset{(.00378)}{.00333}\, wkends - \underset{(.0034)}{.0212}\, unem$$

$$- \underset{(.0126)}{.0538}\, spdlaw + \underset{(.0142)}{.0954}\, beltlaw$$

$n = 108$, $R^2 = .910$

The negative coefficient on *unem* makes sense if we view *unem* as a measure of economic activity. As economic activity increases – *unem* decreases – we expect more driving, and therefore more accidents. The estimate that a one percentage point increase in the unemployment rate reduces total accidents by about 2.1%. A better economy does have costs in terms of traffic accidents.

(iv) At least initially, the coefficients on *spdlaw* and *beltlaw* are not what we might expect. The coefficient on *spdlaw* implies that accidents dropped by about 5.4% *after* the highway speed limit was increased from 55 to 65 miles per hour. There are at least a couple of possible explanations. One is that people because safer drivers after the increased speed limiting, recognizing that the must be more cautious. It could also be that some other change – other than the increased speed limit or the relatively new seat belt law – caused lower total number of accidents, and we have not properly accounted for this change.

The coefficient on *beltlaw* also seems counterintuitive at first. But, perhaps people became less cautious once they were forced to wear seatbelts.

(v) The average of *prcfat* is about .886, which means, on average, slightly less than one percent of all accidents result in a fatality. The highest value of *prcfat* is 1.217, which means there was one month where 1.2% of all accidents resulting in a fatality.

(vi) As in part (iii), I do not report the coefficients on the time trend and seasonal dummy variables:

$$\widehat{prcfat} = \underset{(.103)}{1.030} + \ldots + \underset{(.00616)}{.00063}\, wkends - \underset{(.0055)}{.0154}\, unem$$

$$+ \underset{(.0206)}{.0671}\, spdlaw - \underset{(.0232)}{.0295}\, beltlaw$$

$n = 108$, $R^2 = .717$

Higher speed limits are estimated to increase the percent of fatal accidents, by .067 percentage points. This is a statistically significant effect. The new seat belt law is estimated to decrease the percent of fatal accidents by about .03, but the two-sided p-value is about .21.

Interestingly, increased economic activity also increases the percent of fatal accidents. This may be because more commercial trucks are on the roads, and these probably increase the chance that an accident results in a fatality.

C10.13 (i) The estimated equation is

$$\widehat{gwage232} = \underset{(.0004)}{.0022} + \underset{(.001)}{.151}\, gmwage + \underset{(.082)}{.244}\, gcpi$$

$n = 611$, $R^2 = .293$

The coefficient on *gmwage* implies that a one percentage point growth in the minimum wage is estimated to increase the growth in *wage*232 by about .151 percentage points.

(ii) When 12 lags of *gmwage* are added, the sum of all coefficients is about .198, which is somewhat higher than the .151 obtained from the static regression. Plus, the F statistic for lags 1 through 12 given p-value = .058, which shows they are jointly, marginally statistically significant. (Lags 8 through 12 have fairly large coefficients, and some individual t statistics are significant at the 5% level.)

(iii) The estimated equation is

$$\widehat{gemp232} = \underset{(.0010)}{-.0004} - \underset{(.0228)}{.0019}\, gmwage - \underset{(.1938)}{.0055}\, gcpi$$

$n = 611$, $R^2 = .000$

The coefficient on *gmwage* is puny with a very small t statistic. In fact, the R-squared is practically zero, which means neither *gmwage* nor *gcpi* has any effect on employment growth in sector 232.

(iv) Adding lags of *gmwage* does not change the basic story. The F test of joint significance of *gmwage* and lags 1 through 12 of *gmwage* gives p-value = .439. The coefficients change sign and none is individually statistically significant at the 5% level. Therefore, there is little evidence that minimum wage growth affects employment growth in sector 232, either in the short run or the long run.