equation, and the OLS standard errors almost certainly underestimate the true standard deviation in $\beta_{EZ}$. This makes the usual confidence interval for $\beta_{EZ}$ and $t$ statistics and invalid.

(ii) We can use the method in Section 12.5 to obtain an approximately valid standard error. [See equation (12.43).] While we might use $g = 2$ in equation (12.42), with monthly data we might want to try a somewhat longer lag, maybe even up to $g = 12$.

12.6 With the strong heteroskedasticity in the errors it is not too surprising that the robust standard error for $\hat{\beta}_1$ differs from the OLS standard error by a substantial amount: the robust standard error is almost 82% larger. Naturally, this reduces the $t$ statistic. The robust $t$ statistic is $0.059/0.069 \approx 0.86$, which is even less significant than before. Therefore, we conclude that, once heteroskedasticity is accounted for, there is very little evidence that $return_{t-1}$ is useful for predicting $return_t$.

SOLUTIONS TO COMPUTER EXERCISES

12.7 Regressing $\hat{u}_t$ on $\hat{u}_{t-1}$, using the 69 available observations, gives $\hat{\rho} \approx 0.292$ and $se(\hat{\rho}) \approx 0.118$. The $t$ statistic is about 2.47, and so there is significant evidence of positive AR(1) serial correlation in the errors (even though the variables have been differenced). This means we should view the standard errors reported in equation (11.27) with some suspicion.

12.8 (i) After estimating the FDL model by OLS, we obtain the residuals and run the regression $\hat{u}_t$ on $\hat{u}_{t-1}$, using 272 observations. We get $\hat{\rho} \approx 0.503$ and $t_{\hat{\rho}} \approx 9.60$, which is very strong evidence of positive AR(1) correlation.

(ii) When we estimate the model by iterated C-O the LRP is estimated to be about 1.110.

(iii) We use the same trick as in Problem 11.5, except now we estimate the equation by iterated C-O. In particular, write

$$gprice_t = \alpha_0 + \theta_0 gwaage_t + \delta_1 (gwaage_{t-1} - gwaage_t) + \delta_2 (gwaage_{t-2} - gwaage_t)$$
$$+ \ldots + \delta_{12} (gwaage_{t-12} - gwaage_t) + u_t,$$

where $\theta_0$ is the LRP and $\{u_t\}$ is assumed to follow an AR(1) process. Estimating this equation by C-O gives $\hat{\theta}_0 \approx 1.110$ and $se(\hat{\theta}_0) \approx 0.191$. The $t$ statistic for testing $H_0: \theta_0 = 1$ is $(1.110 - 1)/0.191 \approx 0.58$, which is not close to being significant at the 5% level. So the LRP is not statistically different from one.

12.9 (i) The test for AR(1) serial correlation gives (with 35 observations) $\hat{\rho} \approx -0.110$, $se(\hat{\rho}) \approx 0.175$. The $t$ statistic is well below one in absolute value,
so there is no evidence of serial correlation in the accelerator model. If we view the test of serial correlation as a test of dynamic misspecification, it reveals no dynamic misspecification in the accelerator model.

(ii) It is worth emphasizing that, if there is little evidence of AR(1) serial correlation, there is no need to use feasible GLS (Cochrane-Orcutt or Prais-Winsten).

12.10 (i) After obtaining the residuals $\hat{u}_t$ from equation (11.16) and then estimating (12.48), we can compute the fitted values $\hat{h}_t = 4.66 - 1.104 \cdot \text{return}_t$ for each $t$. This is easily done in a single command using most software packages. It turns out that 12 of 689 fitted values are negative. Among other things, this means we cannot directly apply weighted least squares using the heteroskedasticity function in (12.48).

(ii) When we add $\text{return}^2_{t-1}$ to the equation we get

$$\hat{u}_t^2 = 3.26 - .789 \cdot \text{return}_{t-1} + .297 \cdot \text{return}^2_{t-1} + \text{residual}_t$$

$$n = 689, R^2 = .130.$$ 

So the conditional variance is a quadratic in $\text{return}_{t-1}$, in this case a U-shape that bottoms out at $.789/[(2(.297))] \approx 1.33$. In this case, there are no fitted values less than zero.

(iii) Given our finding in part (ii) we can use WLS with the $\hat{h}_t$ obtained from the quadratic heteroskedasticity function. When we apply WLS to equation (12.47) we obtain $\hat{\beta}_0 \approx .155$ (se $\approx .078$) and $\hat{\beta}_1 \approx .039$ (se $\approx .046$). Thus the coefficient on $\text{return}_{t-1}$, once weighted least squares has been used, is even less significant ($t$ statistic $\approx .85$) than when we used OLS.

(iv) To obtain the WLS using an ARCH variance function we first estimate the equation in (12.51) and obtain the fitted values, $\hat{h}_t$. The WLS estimates are now $\hat{\beta}_0 \approx .159$ (se $\approx .076$) and $\hat{\beta}_1 \approx .024$ (se $\approx .047$). The coefficient and $t$ statistic are even smaller. Therefore, once we account for heteroskedasticity via one of the WLS methods, there is virtually no evidence that $E(\text{return}_t \mid \text{return}_{t-1})$ depends linearly on $\text{return}_{t-1}$.

12.11 (i) Using the data only through 1992 gives

$$\text{dem\_wins} = .441 - .473 \cdot \text{partyWH} + .479 \cdot \text{incum}$$

$$+ .059 \cdot \text{partyWH\_gnews} - .024 \cdot \text{partyWH\_inf}$$

$$n = 20, R^2 = .437, R^2 = .287$$
The largest $t$ statistic is on $incum$, which is estimated to have a large effect on the probability of winning. But we must be careful here. $incum$ is equal to 1 if a Democratic incumbent is running and -1 if a Republican incumbent is running. Similarly, $partyWH$ is equal to 1 if a Democrat is currently in the White House and -1 if a Republican is currently in the White House. So, for an incumbent Democrat running, we must add the coefficients on $partyWH$ and $incum$ together, and this nets out to about zero.

The economic variables are less statistically significant than in equation (10.23). The $gnews$ interaction has a $t$ statistic of about 1.64, which is significant at the 10% level against a one-sided alternative. (Since the dependent variable is binary, this is a case where we must appeal to asymptotics. Unfortunately, we have only 20 observations.) The inflation variable has the expected sign but is not statistically significant.

(ii) There are two fitted values less than zero, and two fitted values greater than one.

(iii) Out of the 10 elections with $demwins = 1$, 8 of these are correctly predicted. Out of the 10 elections with $demwins = 0$, 7 are correctly predicted. So 15 out of 20 elections through 1992 are correctly predicted. (But remember, we used data from these years to obtain the estimated equation.)

(iv) The explanatory variables are $partyWH = 1$, $incum = 1$, $gnews = 3$, and $inf = 3.019$. Therefore, for 1996,

$$dem\hat{wins} = .441 - .473 + .479 + .059(3) - .024(3.019) \approx .552.$$  

Because this is above .5, we would have predicted that Clinton would win the 1996 election, as he did.

(v) The regression of $\hat{u}_t$ on $\hat{u}_{t-1}$ produces $\hat{\rho} \approx -.164$ with heteroskedasticity-robust standard error of about .195. (Because the LPM contains heteroskedasticity, testing for AR(1) serial correlation in an LPM generally requires a heteroskedasticity-robust test.) Therefore, there is little evidence of serial correlation in the errors. (And, if anything, it is negative.)

(vi) The heteroskedasticity-robust standard errors are given in [·] below the usual standard errors:

\[
\begin{align*}
dem\hat{wins} = & \quad .441 - .473 \quad partyWH + .479 \quad incum \\
& \quad (.107) \quad (.354) \quad (.205) \\
& \quad (.086) \quad (.301) \quad (.185) \\
+ & \quad .059 \quad partyWH \cdot gnews - \quad .024 \quad partyWH \cdot inf \\
& \quad (.036) \quad (.028) \\
& \quad (.030) \quad (.019)
\end{align*}
\]

\[n = 20, \quad R^2 = .437, \quad \bar{R}^2 = .287.\]
In fact, all heteroskedasticity-robust standard errors are less than the usual OLS standard errors, making each variable more significant. For example, the $t$ statistic on $\text{partyWH}\cdot\text{gnews}$ becomes about 1.97, which is notably above 1.64. But we must remember that the standard errors in the LPM have only asymptotic justification. With only 20 observations it is not clear we should prefer the heteroskedasticity-robust standard errors to the usual ones.

12.12 (i) The regression $\hat{u}_t$ on $\hat{u}_{t-1}$ (with 35 observations) gives $\hat{\rho} \approx -0.089$ and $\text{se}(\hat{\rho}) \approx 0.178$; there is no evidence of AR(1) serial correlation in this equation, even though it is a static model in the growth rates.

(ii) We regress $g_{ct}$ on $g_{c,t-1}$ and obtain the residuals, $\hat{u}_t$. Then, we regress $\hat{u}_t^2$ on $g_{c,t-1}$ and $g_{c,t-1}^2$ (using 35 observations), the $F$ statistic (with 2 and 32 df) is about 1.08. The $p$-value is about .352, and so there is little evidence of heteroskedasticity in the AR(1) model for $g_{ct}$. This means that we need not modify our test of the PIH by correcting somehow for heteroskedasticity.