

STUDENTS' RESOURCE GUIDE TO ACCOMPANY

**APPLIED ECONOMETRIC TIME SERIES
(4th edition)**

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This version of the guide is for student users of RATS and EVIEWS

PREFACE

This Students' Manual is designed to accompany the fourth edition of Walter Enders' *Applied Econometric Time Series (AETS)*. As in the first edition, the text instructs by induction. The method is to take a simple example and build towards more general models and econometric procedures. A large number of examples are included in the body of each chapter. Many of the mathematical proofs are performed in the text and detailed examples of each estimation procedure are provided. The approach is one of learning-by-doing. As such, the mathematical questions and the suggested estimations at the end of each chapter are important.

The aim of this manual is NOT to provide the answers to each of the mathematical problems. The questions are answered in great detail in the Instructors' version of the manual. If your instructor desire, he/she may provide you with the answers. Instead, the goal of the manual is to get you "up and running" on RATS or EVIEWS. The manual does contain the code or workfiles that you can use to read the data sets. Nevertheless, you will have all of the data to obtain the results reported in the 'Questions and Exercises' sections of *AETS*. Even if your instructor does not assign the exercises, I encourage you to work through as many of these exercises as possible. RATS users should also download the powerpoint slides for RATS users on time-series.net.

There were several factors leading me to provide the partial programs for RATS and EVIEWS users. First, two versions of the RATS Programming Manual can be downloaded (at no charge) from www.estima.com/enders or from www.time-series.net. The two Programming Manuals provide a complete discussion of many of the programming tasks used in time-series econometrics. EVIEWS was included since it is a popular package that allows users to produce almost all of the results obtained in the text. Adobe Acrobat allows you to copy a program from the *.pdf version of this manual and paste it directly into RATS. EVIEWS is a bit different. As such, I have created EVIEWS workfiles for almost all of the exercises in the text. This manual describes the contents of each workfile and how each file was created.

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CHAPTER 1

DIFFERENCE EQUATIONS

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APPENDIX 1.2 Characteristic Roots in Higher-Order Equations

LEARNING OBJECTIVES

1. Explain how stochastic difference equations can be used for forecasting and illustrate how such equations can arise from familiar economic models.
2. Explain what it means to *solve* a difference equation.
3. Demonstrate how to find the solution to a stochastic difference equation using the iterative method.
3. Demonstrate how to find the homogeneous solution to a difference equation.
4. Illustrate the process of finding the homogeneous solution.
5. Show how to find homogeneous solutions in higher order difference equations.
7. Show how to find the particular solution to a deterministic difference equation.
8. Explain how to use the Method of Undetermined Coefficients to find the particular solution to a stochastic difference equation.
9. Explain how to use lag operators to find the particular solution to a stochastic difference equation.

Key Concepts

It is essential to understand that difference equations are capable of capturing the types of dynamic models used in economics and political science. Towards this end, in my own classes, I simulate a number of series and discuss how their dynamic properties depend on the parameters of the data-generating process. Next, I show the students a number of macroeconomic variables--such as real GDP, real exchange rates, interest rates, and rates of return on stock prices--and ask them to think about the underlying dynamic processes that might be driving each variable. I also ask them think about the economic theory that bears on the each of the variables. For example, the figure below shows the three real exchange rate series used in Figure 3.5. You might see a tendency for the series to revert to a long-run mean value. Nevertheless, the statistical evidence that real exchange rates are actually mean reverting is debatable. Moreover, there is no compelling theoretical reason to believe that purchasing power parity holds as a long-run phenomenon. The classroom discussion might center on the appropriate way to model the tendency for the levels to meander. At this stage, the precise models are not important. The objective is for you to conceptualize economic data in terms of difference equations.

It is also important to understand the distinction between convergent and divergent solutions. Be sure to emphasize the relationship between characteristic roots and the convergence or divergence of a sequence. Much of the current time-series literature focuses on the issue of unit roots. Question 5 at the end of this chapter is designed to preview this important issue. The tools to emphasize are the **method of undetermined coefficients** and **lag operators**.

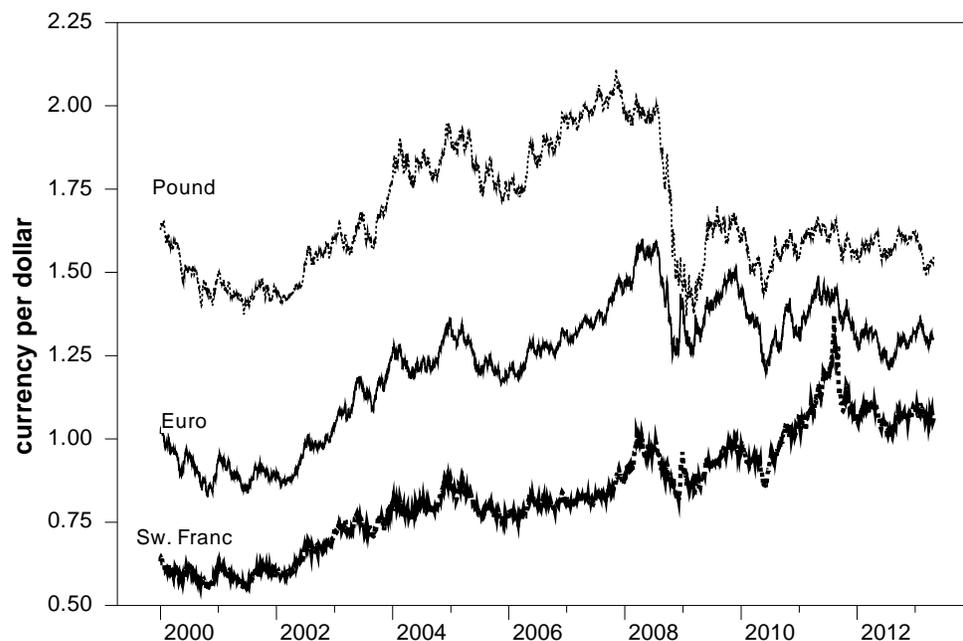


Figure 3.5: Daily Exchange Rates (Jan 3, 2000 - April 4, 2013)

CHAPTER 2

STATIONARY TIME-SERIES MODELS

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Appendix 2.2: Model Selection Criteria

LEARNING OBJECTIVES

1. Describe the theory of stochastic linear difference equations
2. Develop the tools used in estimating ARMA models.
3. Consider the time-series properties of stationary and nonstationary models.
4. Consider various test statistics to check for model adequacy. Several examples of estimated ARMA models are analyzed in detail. It is shown how a properly estimated model can be used for forecasting.
5. Derive the theoretical autocorrelation function for various ARMA processes
6. Derive the theoretical partial autocorrelation function for various ARMA processes
7. Show how the Box–Jenkins methodology relies on the autocorrelations and partial autocorrelations in model selection.
8. Develop the complete set of tools for Box–Jenkins model selection.
9. Examine the properties of time-series forecasts.
10. Illustrate the Box–Jenkins methodology using a model of the term structure of interest rates.
11. Show how to model series containing seasonal factors.
12. Develop diagnostic testing for model adequacy.
13. Show that combined forecasts typically outperform forecasts from a single model.

Improving Your Forecasts

At several points in the text, I indicate that forecasting is a blend of the scientific method and art. I try to stress that there are several guidelines that can be very helpful in selecting the most appropriate forecasting model:

1. Looking at the time path of a series is the single most important step in forecasting the series. Examining the series allows you to see if it has a clear trend and to get a reasonable idea if the trend is linear or nonlinear. Similarly, a series may or may not have periods of ‘excess’ volatility. Outliers and other potential problems with the data can often be revealed by simply looking at the data. If the series does not seem to be stationary, there are several transformations (see below) that can be used to produce a series that is likely to be covariance stationary.
2. In most circumstances, there will be several plausible models that fit the data. The in-sample and out-of sample properties of such models should be thoroughly compared.
3. It is standard to plot the forecasts in the same graph as the series being forecasted. Sometimes it is desirable to place confidence intervals around the forecasted values. If you chose a transformation of the series [e.g., $\log(x)$] you should forecast the values of the series, not the transformed values.
4. The Box-Jenkins method will help you select a reasonable model. The steps in the Box-Jenkins methodology entail:

- **Identification**

Graph the data—see (1) above—in order to determine if any transformations are necessary (logarithms, differencing, ...). Examine the ACF and the PACF of the transformed data in order to determine the plausible models.

- **Estimation**

Estimate the plausible models and select the best. You should entertain the possibility of several models and estimate each. The ‘best’ will have coefficients that are statistically significant and a good “fit” (use the *AIC* or *SBC* to determine the fit).

- **Diagnostic Checking**

Examine the ACF and PACF of the residuals to check for significant autocorrelations. Use the Q-statistics to determine if groups of autocorrelations are statistically significant. Other diagnostic checks include (i) out-of-sample forecasting of known data values (ii) splitting the sample, and (iii) overfitting (adding a lagged value that should be insignificant). You can also check for parameter instability and structural change using the methods discussed in Section 12.

- **Forecasting**

Use the methods discussed in Section 9 to compare the out-of-sample forecasts of the alternative models.

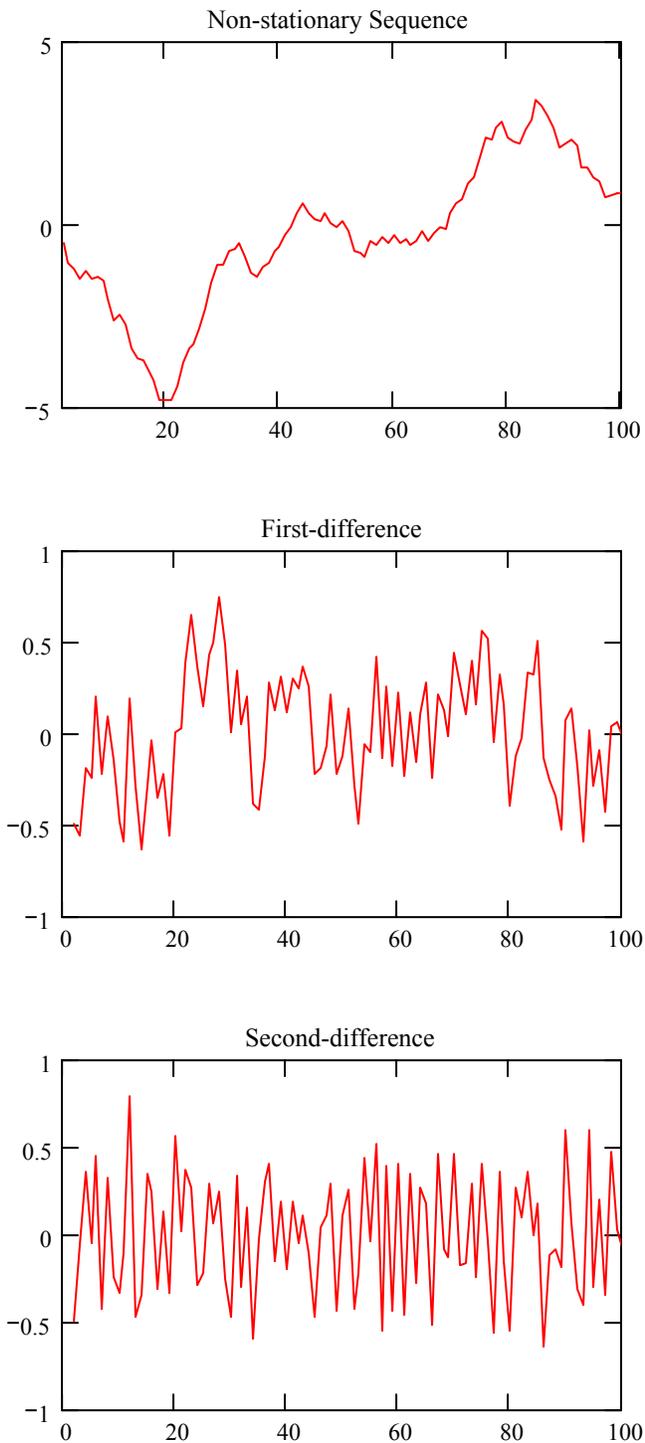
5. My own view is that too many econometricians (students and professionals) overfit the data by including marginally significant intermediate lags. For example, with quarterly data, someone might fit an ARMA model with AR coefficients at lags 1, 4 and 9 and MA an coefficient at lag 7. Personally, I do not think that such models make any sense. As suggested by the examples of the interest rate spread and the data in the file SIM_2.XLS, fitting isolated lag coefficients is highly problematic.

Transforming the Variables: I use Figure M2–1 to illustrate the effects of differencing and over-differencing. The first graph depicts 100 realizations of the unit root process $y_t = 1.5y_{t-1} - 0.5y_{t-2} + \varepsilon_t$. If you examine the graph, it is clear there is no tendency for mean reversion. This non-stationary series has a unit root that can be eliminated by differencing. The second graph in the figure shows the first-difference of the $\{y_t\}$ sequence: $\Delta y_t = 0.5\Delta y_{t-1} + \varepsilon_t$. The positive autocorrelation ($\rho_1 = 0.5$) is reflected in the tendency for large (small) values of Δy_t to be followed by other large (small) values. It is simple to make the point that the $\{\Delta y_t\}$ sequence can be estimated using the Box-Jenkins methodology. It is obvious to students that the ACF will reflect the positive autocorrelation. The third graph shows the second difference: $\Delta^2 y_t = -0.5\Delta^2 y_{t-1} + \varepsilon_t - \varepsilon_{t-1}$. Students are quick to understand the difficulties of estimating this over-differenced series. Due to the extreme volatility of the $\{\Delta^2 y_t\}$ series, the current value of $\Delta^2 y_t$ is not helpful in

predicting $\Delta^2 y_{t+1}$.

The effects of logarithmic data transformations are often taken for granted. I use Figure M2–2 to illustrate the effects of the Box-Cox transformation. The first graph shows 100 realizations of the simulated AR(1) process: $y_t = 5 + 0.5y_{t-1} + \varepsilon_t$. The $\{\varepsilon_t\}$ series is precisely the same as that used in constructing the graphs in Figure M2–1. In fact, the only difference between the middle graph of Figure M2–1 and the first graph of Figure M2–2 involves the presence of the intercept term. The effects of a logarithmic transformation can be seen by comparing the two left-hand-side graphs of Figure M2–2. It should be clear that the logarithmic transformation smooths the series. The natural tendency is for students to think smoothing is desirable. However, I point out that actual data (such as asset prices) can be quite volatile and that individuals may respond to the volatility of the data and not the logarithm of the data. Thus, there may be instances in which we do not want to reduce the variance actually present in the data. At this time, I mention that the material in Chapter 3 shows how to estimate the conditional variance of a series. Two Box-Cox transformations are shown in the right-hand-side graphs of Figure M2–2. Notice that decreasing λ reduces variability and that a small change in λ can have a pronounced effect on the variance.

Figure M2–1: The Effects of Differencing



The $\{y_t\}$ sequence was constructed as:

$$y_t = 1.5y_{t-1} - 0.5y_{t-2} + \varepsilon_t$$

The unit root means that the sequence does not exhibit any tendency for mean reversion.

The first-difference of the $\{y_t\}$ sequence is:

$$\Delta y_t = 0.5\Delta y_{t-1} + \varepsilon_t$$

The first-difference of $\{\Delta y_t\}$ is a stationary AR(1) process such that $a_1 = 0.5$.

The second-difference of the sequence is:

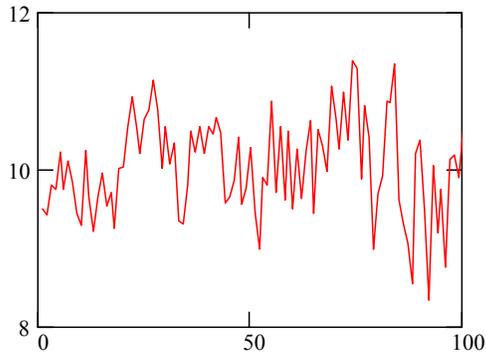
$$\Delta^2 y_t = -0.5\Delta^2 y_{t-1} + \varepsilon_t - \varepsilon_{t-1}$$

The over-differenced $\{\Delta^2 y_t\}$ sequence has an invertible error term.

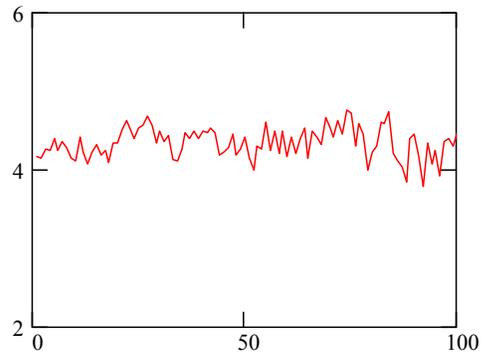
Figure M2–2: Box-Cox Transformations

$$y_t = 5 + 0.5y_{t-1} + \varepsilon_t$$

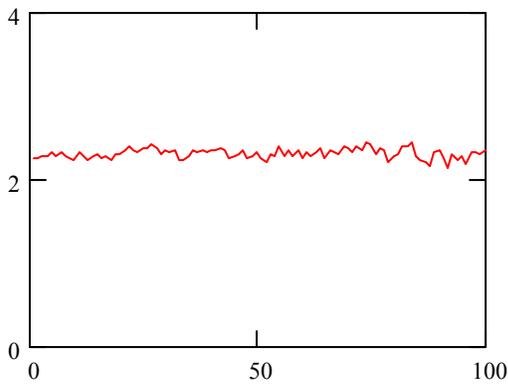
$$\lambda = 0.5$$



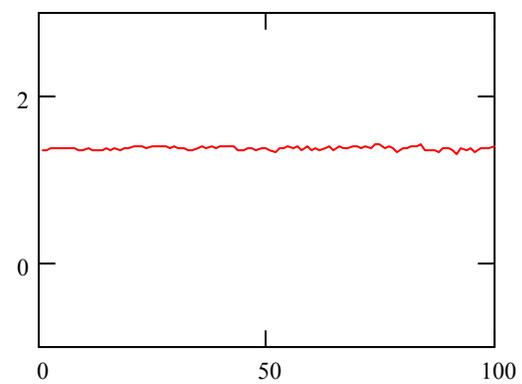
Standard Deviation = 0.609



Standard Deviation = 0.193



Standard Deviation = 0.061



Standard Deviation = 0.019

The first graph shows 100 realizations of a simulated AR(1) process; by construction, the standard deviation of the $\{y_t\}$ sequence is 0.609. The next three graphs show the results of Box-Cox transformations using values of $\lambda = 0.5$, 0.0, and -0.5 , respectively. You can see that decreasing λ acts to smooth the sequence.

Selected Answers to Questions

8. The file entitled SIM_2.XLS contains the simulated data sets used in this chapter. The first column contains the 100 values of the simulated AR(1) process used in Section 7. This first series is entitled Y1. The following programs will perform the tasks indicated in the text. Due to differences in data handling and rounding, your answers need only approximate those presented in the text.

Initial Program for RATS Users

```
all 100 ;* The first 3 lines read in the data set
open data a:\sim_2.xls ;* Modify this if your data is not on drive a:
data(format=xls,org=obs)

cor(partial=pacf,qstats,number=24,span=8) y1 ;* calculates the ACF, PACF, and Q-statistics
graph 1 ;* plots the simulated series
# y1

boxjenk(ar=1) y1 / resid ;* estimates an AR(1) model and saves the
;* residuals in the series called resid
```

Notes for EViews Users

The file *aets4_ch2_question8910.wf1* contains the data 8, 9, and 10. Note that the file contains the series y1, y2, and y3. The descriptions of the variables and tables should be self evident. The EViews versions of Figures 2.3 and 2.4 are contained in the file as well.

There are several important points to note:

1. In the Appendix, it is shown how an MA model can be estimated using maximum likelihood techniques by assuming the initial value ε_0 is equal to zero. This immediately generalizes to higher order processes. However, given the initial estimates of the AR and MA coefficients it is also possible to “backcast” the initial value(s). By default, EViews “backcasts” these initial values. **As such, when estimating models with MA terms, the estimated coefficients and their standard errors (and *t*-statistics) will be slightly different from those reported in the text.**

2. Backcasting can be turned off. This is particularly useful if you are having problems obtaining solutions.

3. As described in the USER’S GUIDE, there are two ways to estimate $I(1)$ models. Suppose that you want to the variable x as an ARIMA(1,1,1) process. The first method is to GENERATE a differenced series using the difference operator as in:

```
series dx = d(x).
ls dx c ar(1) ma(1)
```

The second is to use the difference operator directly in the command as in

```
ls d(x) c ar(1) ma(1)
```

4. In EViews, the reported values of the AIC and SBC are calculated as:

$$-2(\log \text{likelihood}/T) + 2n/T \text{ and } -2(\log \text{likelihood}/T) + n\log(T)/T.$$

In Chapter 2, these values are reported as

$$-2RSS + 2n \text{ and } -2RSS + n\log(T)$$

As such, the values of the AIC and SBC reported in the text will differ from those reported in EVIEWS. Nevertheless, as shown in Question 7 above, either reporting method will select the same model. Note that the method used by EVIEWS assumes normality whereas the method used in the text is distribution free (which can be desirable when nonlinear least squares estimation methods are used).

9. The second column in file entitled SIM_2.XLS contains the 100 values of the simulated ARMA(1, 1) process used in Section 7. This series is entitled Y2. The following programs will perform the tasks indicated in the text. Due to differences in data handling and rounding, your answers need only approximate those reported in the text.

EViers Users should see the notes to Question 8 above.

Sample Program for RATS Users

```
all 100 ;* The first 3 lines read in the data set
open data a:\sim_2.xls ;* Modify this if your data is not on drive a:
data(format=xls,org=obs)
```

```
cor(partial=pacf,qstats,number=24,span=8) y2 ;* calculates the ACF, PACF, and Q-statistics
graph 1 ;* plots the simulated series
# y2
```

*RATS contains a procedure to plot autocorrelation and partial autocorrelations. To use the *procedure use the following two program lines:

```
source(noecho) c:\winrats\bjident.src ;* assuming RATS is in a directory called C:\WINRATS
@bjident y2
```

```
boxjenk(ar=1) y2 / resids ;* estimates an AR(1) model and saves the residuals
cor(number=24,partial=partial,qstats,span=8) resids / cors
compute aic = %nobs*log(%rss) + 2*%nreg
compute sbc = %nobs*log(%rss) + %nreg*log(%nobs)
display 'aic = ' AIC 'sbc = ' sbc
```

*To compare the MA(2) to the ARMA(1, 1) you need to be a bit careful. For a head-to-head *comparison, you need to estimate the models over the same sample period. The ARMA(1, 1) *uses 99 observations while the MA(2) uses all 100 observations.

10. The third column in SIM_2.XLS contains the 100 values of a AR(2) process; this series is entitled Y3. The following programs will perform the tasks indicated in the text. Due to differences in data handling and rounding, your answers need only approximate those reported in the text.

EViers Users should see the notes to Question 8 above.

Sample Program for RATS Users

Use the first three lines from Question 7 or 8 to read in the data set. To graph the series use:

```
graph 1 ; # y3 ;* plots the simulated series
```

boxjenk(ar=1) y3 / resids ;* estimates an AR(1) model and saves the residuals

*To estimate the AR(2) model with the single MA coefficient at lag 16 use:

boxjenk(ar=2,ma=||16||) y3 / resids

11. If you have not already done so, download the *Programming Manual* that accompanies this text and the data set QUARTERLY.XLS.

a. Section 2.7 examines the price of finished goods as measured by the PPI. Form the logarithmic change in the PPI as: $dly_t = \log(ppi_t) - \log(ppi_{t-1})$. Verify that an AR(1,3) model of the dly_t series has a better in-sample fit than an AR(3) or an ARMA(1,1) specification.

EViews Users:

The file *aets4_ch2_question11.wfl* contains the variables *ppi* and *dly*.

Programs for RATS USERS

*Read in the data set using:

```
cal(q) 1960 1
all 2012:4
open data c:\aets4\quarterly.xls
data(org=obs,format=xls)
tab(picture=* ##)
* Create  $dly_t = \log(ppi_t) - \log(ppi_{t-1})$ .
log ppi / ly
dif ly / dly
```

* Estimate the AR(3) model using

```
box(constant,ar=3) dly / resids
```

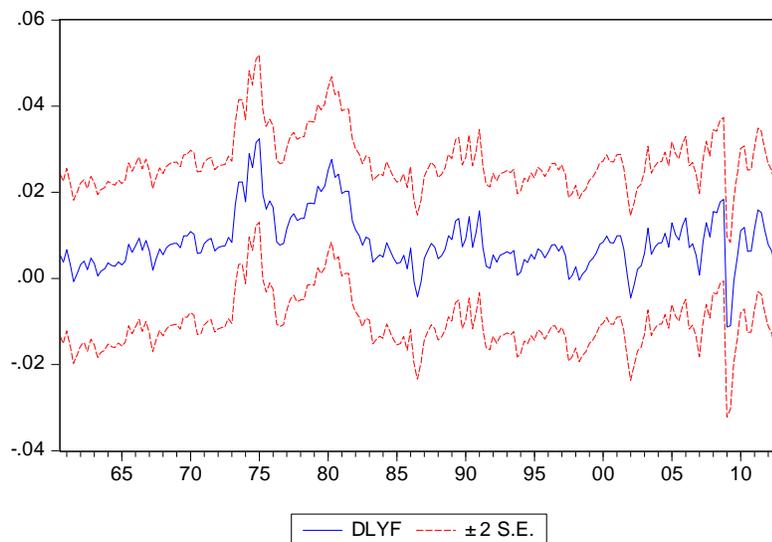
* For each, compare the fit using: **(Be sure to estimate each over the same sample period)**

```
com aic = %nobs*log(%rssl) + 2*(%nreg)
com sbc = %nobs*log(%rssl) + (%nreg)*log(%nobs)
display "aic = " aic "bic = " sbc
```

b. How does the out-of-sample fit of the AR(1,3) compare to that of the ARMA(1,1)?

Notes for EViews Users

The file *aets4_ch2_question11.wfl* for instructors contains the one-step-ahead forecasts and a ± 2 standard error band for the ARMA(1,1) model. The graph is entitled *graph_q11* and the forecasts are in the series *dlyf*. note that in creating the forecasts, use the option *STATIC*. The dynamic forecasts are the multi-step ahead forecasts conditional on the initial observation. For example, click on the equation names *eq_arma11* and then click on *Forecast*. The *Method* options allows you to chose either method. If you chose the entire sample period (the default) you should obtain:



Forecast:	DLYF
Actual:	DLY
Forecast sample:	1960Q1 2012Q4
Adjusted sample:	1960Q3 2012Q4
Included observations:	210
Root Mean Squared Error	0.009333
Mean Absolute Error	0.006253
Mean Abs. Percent Error	109.0738
Theil Inequality Coefficient	0.373616
Bias Proportion	0.000003
Variance Proportion	0.266415
Covariance Proportion	0.733582

Repeat for the other series.

Programs for RATS USERS

* For the ARMA(1,1) create the one-step ahead forecasts beginning from 2000:2:

```
set error2 2000:3 2012:4 = 0.0
do t = 2000:2,2012:3
    box(constant,ar=1,ma=1,define=arma,nopri) dly * t
    ufor(equation=arma) f2 t+1 t+1
    com error2(t+1) = dly(t+1) - f2(t+1)
end do t
table / error2
```

c. What is the problem in comparing the out-of-sample fit of the AR($\|1,3\|$) to that of the AR(3)?

The models are nested so that the usual DM test is not appropriate.

d. Experiment with an AR(5) and an ARMA(2,1) model (see Exercise 2.1 on page 32 of the programming manual) to see how they compare to the AR($\|1,3\|$).

* Estimate the ARMA(2,1) using:
`box(ar=2,ma=1,constant) dly / resid`

Be sure to compute the residual autocorrelations, the AIC and the ABC to that of the AR($\|1,3\|$).

12. Section 2.9 of the *Programming Manual* that accompanies considers several seasonal models of the variable Currency (*Curr*) on the data set QUARTERLY.XLS.

a. First-difference $\log(\text{curr}_t)$ and obtain the ACF and PACF of the resultant series. Does the seasonal pattern best reflect an AR, MA or a mixed pattern? Why is there a problem in estimating the first-difference using the Box-Jenkins methodology? b. Now, obtain the ACF and PACF of the seasonal difference of the first-difference. What is likely the pattern present in the ACF and PACF?

Notes for EViews Users

The file *aets4_ch2_question 12.wfl* contains the series *curr*, *dlcurr* and *dlcurr4*. Note that *dlcurr4* is the differenced and seasonally differenced series generated using

```
dlcurr4 = dlog(curr,1,4)
```

curr_acf is the correlogram of the series *dlcurr* and *dlcurr4* is the correlogram of the series *dlcurr4*.

Programs for RATS USERS

* Read in the data sets using

```
cal(q) 1960 1
```

```
all 2012:4
```

```
open data c:\RatsManual\quarterly.xls
```

```
data(org=obs,format=xls)
```

* Create the appropriate differences

```
log curr / ly
```

```
dif ly / dly
```

```
dif(sdiffs=1,dif=1) ly / m ; * Create the first-difference and seasonal difference
```

13. The file QUARTERLY.XLS contains a number of series including the U.S. index of industrial production (*indprod*), unemployment rate (*urate*), and producer price index for finished goods (*finished*). All of the series run from 1960Q1 to 2008Q1.

a. Exercises with *indprod*.

i. Construct the growth rate of the series as $y_t = \log(\text{indprod}_t) - \log(\text{indprod}_{t-1})$. Since the first few autocorrelations suggest an AR(1), estimate $y_t = 0.0028 + 0.600y_{t-1} + \varepsilon_t$ (the *t*-statistics are 2.96 and 10.95, respectively).

ii. Show that adding an AR term at lag 8 improves the fit and removes some of the serial correlation. What concerns do you have about simply adding an AR(8) term to the industrial production series?

Notes for EViews Users

1. The file *aets4_ch2_question 13.wfl* in the instructors manual contains the answers to parts *a* and *b* of the question. Note that the series *y* was generated as the logarithmic change in industrial production using

```
y = dlog(indprod)
```

The correlogram is in *y_acf*.

SAMPLE PROGRAM FOR RATS USERS

*READ IN THE DATA SET AS ABOVE. Create the growth rate:

```
set ly = log(indprod)
```

```
dif ly / dly
```

*Estimate the AR(1) and examine the residuals

```
lin dly / resids ; # constant dly{1}
```

```
@regcorr
```

b. Exercises with *urate*.

i. Graph the time path and the ACF of the series. Do you have any concerns that the series may not be covariance stationary with normally distributed errors?

ii. Temporarily ignore the issue of differencing the series. Estimate *urate* as an AR(2) process including an intercept. You should find $y_t = 0.226 + 1.65y_{t-1} - 0.683y_{t-2} + \varepsilon_t$

SAMPLE PROGRAM FOR RATS USERS

```
set y = unemp
gra 1 ; # y
```

c. Exercises with *cpicore*.

- i. It is not very often that we need to second-difference a series. However, construct the inflation rate as measured by the core CPI as $dly_t = \log(cpicore_t) - \log(cpicore_{t-1})$. Form the ACF and PACF of the series and indicate why a Box-Jenkins modeler might want to work with the second difference of the logarithm of the core CPI.
- ii. Let $d2ly_t$ denote the second difference of the dly_t series. Find the best model of the $d2ly_t$ series. In particular, show that an MA(1) model fits the data better than an AR(1).
- iii. Does the MA(1) or the AR(1) have better forecasting properties?

Notes for EViews Users

The file *aets4_ch2_question13c.wfl* contains the series and series dly and $dly2$ generated using

```
dly = dlog(cpicore)
dly2 = d(dly)
```

The first few autocorrelations of dly (contained in *acf*) are 0.92, 0.88, and 0.84. The AR(1) model is using the entire data set (see *dly2_ar1*) and the sample period for the MA(1) is restricted to begin in 1960q4 (since 2 observations are lost due to differencing and 1 is lost by estimating an AR(1) model). The STATIC forecasts (i.e., the one step ahead forecasts) from the MA(1) are called *f_mal* and those from the AR(1) are called *f_ar1*.

SAMPLE PROGRAM FOR RATS USERS

* Create the growth rate using:

```
set ly = log(cpicore)
dif ly / dly
```

* Now difference the first-difference:

```
dif dly / d2ly
```

14. The file QUARTERLY.XLS contains U.S. interest rate data from 1960Q1 to 2012Q4. As indicated in Section 10, form the spread by subtracting the T-bill rate from the 5-year rate.

a. Use the full sample period to obtain estimates of the AR(7) and the ARMA(1, 1) model reported in Section 10.

Notes for EViews Users

The file *aets4_ch2_section10.wfl* in the Instructors' Manual contains the results reported in Section 10 of Chapter 2. The file *aets4_ch2_question 14.wfl* contains the answers to both parts of the question. In *aets4_ch2_question 14.wfl*:

f1 and *f2* contain the forecasts from the AR(7) and ARMA(1,1) models

a1 and *a2* are the respective absolute values of forecast errors

e1 and *e2* are the respective values of the squared forecast errors

d_absloss is $a1 - a2$

The DM test of the absolute and squared losses are in *dm_absloss* and *dm_squaredloss*.

Sample Program for RATS Users

*Read in the data set as above and form the spread using:

```
set y = r5 - tbill
```

* Estimate the AR(7) using

```
box(ar=7,constant) y 1961:4 * resid
```

b. Estimate the AR(7) and ARMA(1, 1) models over the period 1960Q1 to 2000Q3. Obtain the one-step-ahead forecasts and the one-step-ahead forecast errors from each.

* Obtain the out-of-sample forecasts for the AR7 using:

```
com h = 50, start = 2012:4-h+1
set f_ar7 start * = 0. do i = 1,h ;
    boxjenk(define=ar7,constant,ar=7,noprint) y * 2012:4-(h+1)+i
    forecast 1 1
    # ar7 f_ar7
end do
```

* Create the regression equations to test for the bias using:

```
lin y ; # constant f_ar7
TEST(NOZEROS)
# 1 2
# 0 1
```

c. Construct the Diebold-Mariano test using the mean absolute error. How do the results compare to those reported in Section 10.

```
set err_ar7 start * = y - f_ar7
set d start * = abs(err_ar7) - abs(err_arma)
sta(noprint) d ; com dbar = %mean , v = %variance ; dis dbar
com dm1 = dbar/( (v/(h-1))**.5 )
dis 'DM(no lags) = ' dm1
```

* Now use robust standard errors

```
lin(robust,lags=5) d ; # constant
```

e. Construct the ACF and PACF of the first-difference of the spread. What type of model is suggested?

15. The file QUARTERLY.XLS contains the U.S. money supply as measured by M1 (M1NSA) and as measured by M2 (M2NSA). The series are quarterly averages over the period 1960:1 to 2012Q:4.

Notes for EViews Users

The file *aets4_ch2_question15.wf1* for the Instructors' Manual contains Figure 2.8 and 2.8. Note that

```
growth_m = 100*dlog(m1nsa)
growth_m2 = dlog(m2nsa)
m = dlog(m1nsa,1,4)
```

Also, *model1*, *model2*, and *model3* yield the results in Table 2.5 of the text. The tables names *part_b*, *part_c* and *part_d* are self-explanatory.

a. Reproduce the results for M1 that are reported in Section 11 of the text.

SAMPLE PROGRAM FOR RATS USERS

```
*READ IN THE DATA SET
cal(q) 1960 1
all 2012:4
```

open data c:\aets4\chapter_2\quarterly.xls
 data(format=xls,org=obs)

* Create the appropriately differenced variable as:
 log m1nsa / lx
 dif(sdiffs=1,dif=1) lx / sdlx

b. How do the three models of M1 reported in the text compare to a model with a seasonal AR(1) term with an additive MA(1) term?
 * Estimate the model

box(ma=1,sar=1) lx 1962:3 * resid

d. Denote the seasonally differenced growth rate of M2NSA by m_{2t} . Estimate an AR(1) model with a seasonal MA term over the 1962:3 to 2014:4 period. You should obtain: $m_{2t} = 0.5412m_{2t-1} + \varepsilon_t - 0.8682\varepsilon_{t-4}$. Show that this model is preferable to (i) an AR(1) with a seasonal AR term, (ii) MA(1) with a seasonal AR term, and (iii) an MA(1) with a seasonal MA term.
 * Now redefine lx so that

log m2nsa / lx
 dif(sdiffs=1,dif=1) lx / sdlx

* Estimate the model using
 box(ar=1,sma=1) sdlx 1962:3 * resid

16. The file labeled Y_BREAK.XLS contained the 150 observations of the series constructed as $y_t = 1 + 0.5y_{t-1} + (1 + 0.1y_{t-1})D_t + \varepsilon_t$ where D_t is a dummy variable equal to 0 for $t < 101$ and equal to 1.5 for $t \geq 101$.

Notes for EViews Users

Unfortunately it is not straightforward to create dummy variables in EViews. One way to create the dummy variable is to use the two instructions below. The first instruction creates the variable *time* using the @trend function. Adding 1 to @trend(1) creates the series 1, 2, 3, Otherwise the first entry for *time* would be zero. The second instruction creates the series *dummy* using the @recode instruction. In essence, @recode is equivalent to an IF instruction in most programming languages. The code below, *dummy* is 0 for all values of *time* <= 100 and is 1 otherwise.

```
series time = @trend(1)+1
series dummy = @recode(time>100,1,0)
```

The file *aets4_ch2_question16.wf1* contains the variable *y_break* and the variable *dummy* generated using the code above. The variable *dummy_y* interacts *dummy* and *y_break*. In the Instructors' Manual EQ01 is the equation containing the model estimated as:

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.601506	0.221870	7.218226	0.0000
Y_BREAK(-1)	0.254493	0.092321	2.756616	0.0066
DUMMY	-0.224420	0.573773	-0.391130	0.6963
DUMMY_Y	0.543273	0.121476	4.472253	0.0000

In contrast, *nobreak* is the model estimated without any of the dummy variables. The file also contains the recursive estimates, the recursive residuals and the cusums. To obtain these estimates, open *EQ01* and select the tab VIEW. Select *Stability Diagnostics* to produce the recursive estimates, recursive residuals and the cusums.

Programs for RATS USERS

OPEN DATA "a:\y_break.xls"

ALL 150

DATA(FORMAT=XLS,ORG=COLUMNS) 1 150 ENTRY y_break

set y = y_break

* DOWNLOAD REGRECUR.SRC from ESTIMA.COM

source c:\rats\regrecur.src

lin y ; # constant y{1}

@regrecursive(cusums,cohist=coeffs,sighist=stddev,sehist=c_sds) resid

CHAPTER 3

MODELING VOLATILITY

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Online

Appendix 3.1 Multivariate GARCH Models is in the *Supplementary Manual*.

Learning Objectives

1. Examine the so-called *stylized facts* concerning the properties of economic time-series data.
2. Introduce the basic ARCH and GARCH models.
3. Show how ARCH and GARCH models have been used to estimate inflation rate volatility.
4. Illustrate how GARCH models can capture the volatility of oil prices, real U.S. GDP, and the interest rate spread.
5. Show how a GARCH model can be used to estimate risk in a particular sector of the economy.
6. Explain how to estimate a time-varying risk premium using the ARCH-M model.
7. Explore the properties of the GARCH(1,1) model and forecasts from GARCH models.
8. Derive the maximum likelihood function for a GARCH process.
9. Explain several other important forms of GARCH models including IGARCH, asymmetric TARARCH, and EGARCH models.
10. Illustrate the process of estimating a GARCH model using the NYSE 100 Index.
11. Show how multivariate GARCH models can be used to capture volatility spillovers.
12. Develop volatility impulse response functions and illustrate the estimation technique using exchange rate data.

Some Key Concepts

1. I use Figure 3-7 (reproduced below) to illustrate ARCH processes. As described in the text, the upper-left-hand graph shows 100 serially uncorrelated and normally distributed disturbances representing the $\{v_t\}$ sequence. These disturbances were used to construct the $\{\varepsilon_t\}$ sequence shown in the upper-right-hand graph. Each value of ε_t was constructed using the formula $\varepsilon_t = v_t[1 + 0.8(\varepsilon_{t-1})]$.

$_1)^2]$. The lower two graphs show the interaction of the ARCH error term and the magnitude of the AR(1) coefficients. Increasing the magnitude of the AR(1) coefficient from 0.0, to 0.2, to 0.9, increased the volatility of the simulated $\{y_t\}$ sequence. For your convenience, a copy of the figure is reproduced below.

2. Instead of assigning Question 4 as a homework assignment, I use the three models to illustrate the properties of an ARCH-M process. Consider the following three models:

Model 1: $y_t = 0.5y_{t-1} + \varepsilon_t$

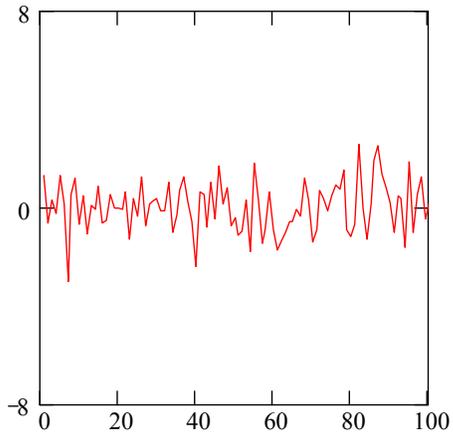
Model 2: $y_t = \varepsilon_t - (\varepsilon_{t-1})^2$

Model 3: $y_t = 0.5y_{t-1} + \varepsilon_t - (\varepsilon_{t-1})^2$

Model 1 is a pure AR(1) process that is familiar to the students. Model 2 is a pure ARCH-M process. When the realized value of ε_{t-1} is large in absolute value, the conditional expectation of y_t is negative: $E_{t-1}y_t = -(\varepsilon_{t-1})^2$. Thus, Model 2 illustrates a simple process in which the conditional mean is

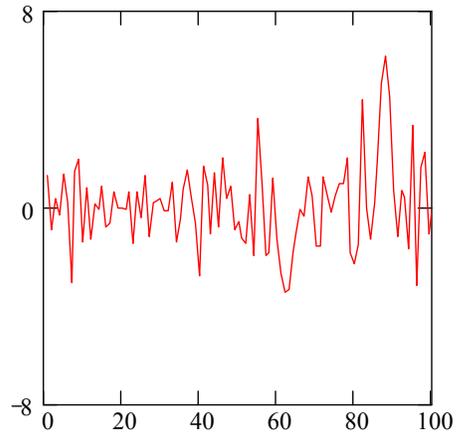
Figure 3.7: Simulated ARCH Processes

White noise process v_t



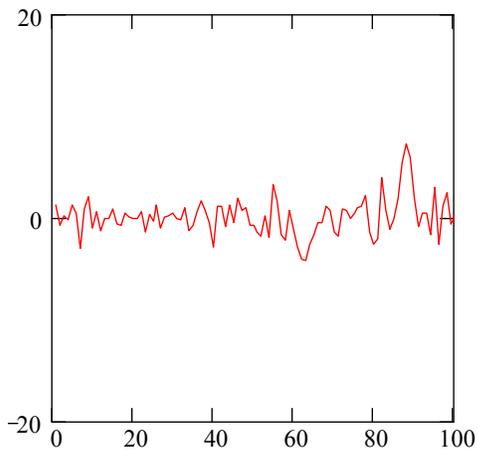
(a)

$$\varepsilon_t = v_t \cdot \sqrt{1 + 0.8 \cdot (\varepsilon_{t-1})^2}$$



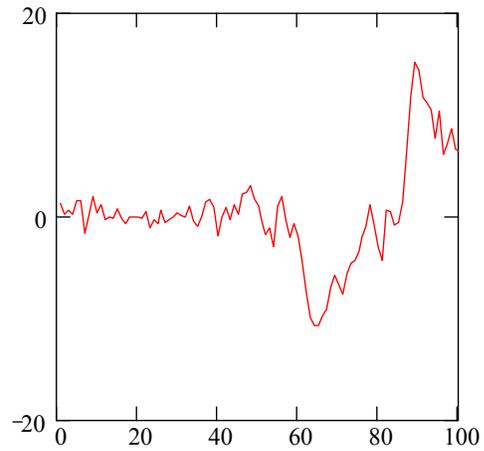
(b)

$$y_t = 0.2y_{t-1} + \varepsilon_t$$



(c)

$$y_t = 0.9y_{t-1} + \varepsilon_t$$



(d)

negatively related to the absolute value of the previous period's error term. Suppose that all values of ε_i for $i \leq 0$ are zero. Now, if the next 5 values of the ε_i sequence are (1, -1, -2, 1, 1), y_i has the time path shown in Figure 3M-1 (see the answer to Question 4 below). I use a projection of Figure 3M-1 to compare the path of the AR(1) and ARCH-M models. Model 3 combines the AR(1) model with the ARCH-M effect exhibited by Model 2. The dotted line shown in Figure 3M-1 shows how the AR(1) and ARCH-M effects interact.

Selected Answers to Questions

5. The file labeled ARCH.XLS contains the 100 realizations of the simulated $\{y_i\}$ sequence used to create the lower right-hand panel of Figure 3.7. The following program will reproduce the reported results.

Notes to EViews Users

1. In the Instructors' Manual answers are contained in the file *aets4_ch2_q5.wfl*. The workfile contains the series *y* and *y_m*. *part_a* contains the estimated AR(1) model and the correlogram of the residuals is in *part_b*. The correlogram of the squared residuals is in *part_c*. The LM tests for ARCH effects is in *part_d* and the ARCH(1) estimate is in *part_e*.
2. To estimate an ARCH-type model in EViews, select **Estimate Equation** from the **Quick** tab. Enter the model of the mean in the box labeled **Equation Specification**. Enter the model of the mean just as you would do for an OLS model. In the lower portion of the **Estimate Equation** box select **ARCH - Autoregressive Conditional Heteroskedasticity**. This will open a second dialogue box in which you can select the order of the GARCH model, and other features of the variance model such as the distribution to use for maximum likelihood estimation and whether to include ARCH-M effects,

Sample Program for RATS Users:

```
all 100 ;* allocates space for 100 observations
open data a:\arch.xls ;* opens the data set assumed to be on drive a:\
data(format=xls,org=obs)
```

* Next, estimate an AR(1) model without an intercept and produce the ACF and PACF.

```
boxjenk(ar=1) y / resid
cor(partial=pacf,qstats,number=24,span=4,dfc=1) resid
```

* Now, define sqresid as the squared residuals from the AR(1) model and construct the ACF
* and PACF of these squared residuals.

```
set sqresid = resid*resid
cor(partial=pacf,qstats,number=24,span=4,dfc=1) sqresid
```

Instead of the GARCH Instruction users of older versions of RATS can use

```
nonlin b1 a0 a1 ;* prepares for a non-linear estimation b1 a0 and a1
frml regresid = y - b1*y{1} ;* defines the residual
frml archvar = a0 + a1*regresid(t-1)**2 ;* defines the variance
frml archlogl = (v=archvar(t)), -0.5*(log(v)+regresid(t)**2/v) ;* defines the likelihood
boxjenk(ar=1) y ;* estimate an AR(1) in order to obtain an initial
compute b1=%beta(1) ;* guess for the value of b1 and a0
compute a0=%seesq, a1=.3 ;* the initial guesses of a0 and a1
* Given the initial guesses and the definition of archlogl, the next line performs the non-
* linear estimation of b1, a0, and a1.
maximize(method=bhhh,recursive,iterations=75) archlogl 3 *
```

6. The second series on the file ARCH.XLS contains 100 observations of a simulated ARCH-M

process. The following programs will produce the indicated results.

Notes to EViews Users

In the Instructors' Manual, the answers are contained in the file *aets4_ch2_q6.wfl*. The workfile contains the series *y* and *y_m*. *part_a* contains the estimated MA(3,6) model and the correlogram of the residuals is in *part_b*. The estimate of the ARCH-M model is in *part_c*.

SAMPLE PROGRAM FOR RATS USERS

all 100

open data a:/arch.xls

data(format=xls,org=obs)

table / y_m ;* The second series on the file is called *y_m*. TABLE produces the desired
;* summary statistics.

* The following instruction produces the graph of the ARCH-M process
graph(header='Simulated ARCH-M Process') 1 ; # y_m

* To estimate the MA(3,6) process and save the residuals as *resids*, use:
boxjenk(constant,ma=3,6) y_m / resids

8. The file RGDP.XLS contains the data used to construct Figures 3.1 and 3.2.

Notes for EViews Users

1. In the Instructors' Manual, the file *aets4_ch3_q8.wfl* contains the answers to the question. The file contains all of the series from the file REAL.XLS. As shown in the file, the series *dly* was generated as $dly = \log(\text{rgdp}) - \log(\text{rgdp}(-1))$ although the equivalent $dly = d\log(\text{rgdp})$ would have been a bit shorter.

2. As discussed in the Answers to Question 2, EViews does not readily create dummy variables. In this program *dummy* was created using

```
dummy = @recode(@date>@dateval("1984Q4"), 1, 0)
```

Note that `@recode` interacts with `@date` and `@dateval` to form the equivalent of an IF statement such that variable *dummy* is 0 until 1983Q4 and is 1 thereafter. The variable *d2* was created using the alternative method of creating dummy variables. First the variable *time* was generated such that

```
time = @trend+1
```

so that *time* = 1, 2, 3, 4, ... Then the following `@recode` instruction was used

```
d2=@recode(time<243, 0, 1)
```

Since observation 243 of *time* corresponds to 2007Q3, the desired dummy is created. Although the first method seems easier here, in other examples using undated variables, it is necessary to use this second method.

3. The file contains the graph of real GDP, reproduces the results on pages 136, and contains the answers to parts a, b, and c. The labeling of each answer should be clear after opening the file.

Sample Program for RATS Users

a. You can read in the data and construct the graphs using:

```
cal(q) 1947 1
```

```
all 2012:4
```

```
open data c:\aets4\real.xls
```

```
data(format=xls,org=obs)
```

*Next create the annualized growth rate using:
log rgdp / ly ; dif ly / dly; set dlya = 400*dly

9. This program produces the results for the NYSE data used in Section 10. In some weeks, there were not five trading days due to holidays and events such as 9/11. The data in the file sets the rate of return equal to zero for such dates. Any capital gain or loss is attributed to the first day after trading resumes.

Notes for EViews Users

1. In the Instructors' Manual the file *nyse(returns).wfl* contains the answers to the questions for this section. The GROUP *spreadsheet* contains the variables *return* and *rate*. The construction of *rate* was discussed above.
2. The table labeled *p160* contains the estimate of *rate* as an AR(2) and *acf_squaredresid* is the ACF of the squared residuals from the AR(2) model.
3. The estimates on pages 160 – 163 are clearly labeled in the file.

Sample Program for RATS Users

* Read in the data using:

```
CAL(daily) 2000 1 3
all 2012:7:16
open data c:\aets4\chapter_3\nyse(returns).xlsx
data(org=obs,format=xlsx)
```

* Create Figure 3.3

```
gra(footer='Figure 3.3: Percentage Change in the NYSE US 100: (Jan 4, 2000 - $
  July 16, 2012)',vla='percentage change',patterns) 1
# rate
```

* Create the histogram using:

```
stat(noprint) rate ; set standard = (rate-%mean)/%variance**.5
@histogram(distri=normal,maxgrid=50) standard
```

10. Use the data of the file EXRATES(DAILY).XLS to estimate a bivariate model of the pound and euro exchange rates.

Notes for EViews Users

1. In the Instructors' Manual, the *workfile aets4_ch3_q10.wfl* contains the answers to this question. The three exchange rates (*euro*, *pound*, and *sw*) and their logarithmic changes (*dleu*, *druk*, and *dls*) are contained in the file. Include *dls* to reproduce the results in the text.
2. In order to estimate the CCC model it is necessary to combine the model of the mean and the format of the variance into a SYSTEM. For the diagonal vech the following code was used:

```
system sys01
sys01.append dleu = c(1)
sys01.append druk = c(2)
sys01.arch @diagvech c(undef) arch(1) garch(1)
```

Hence, the models of the mean are simply constants; $c(1)$ and $c(2)$ are the intercepts for the euro and pound equations, respectively. The last instruction specifies a GARCH(1, 1) process for the conditional variances. Similarly, the SYSTEM instructions for the CCC model are:

```
system sys02
sys02.append dleu = c(1)
sys02.append dluk = c(2)
sys02.arch @ccc c(indef) arch(1) garch(1)
```

These sets of instructions are in the SYSTEM tabs *sys01* and *sys02*. The tabs *diagvech* and *ccc* contain the output.

Sample Program for RATS Users

* The following program will reproduce the results reported in the text. Simply eliminate the Swiss franc from the models below to answer Question 10.

```
OPEN DATA "C:\AETS4\Chapter_3\exrates(daily).xls"
CALENDAR(D) 2000:1:3
ALL 2013:04:26
DATA(FORMAT=XLS,ORG=COLUMNS)
* Fill in the missing values using
set euro = %if(%valid(euro),euro,euro{1})
set pound = %if(%valid(pound),pound,pound{1})
set sw1 = %if(%valid(sw),sw,sw{1})
set sw = 1/sw1 ; Convert to same base currency

*Create the logarithmic changes of the three rates
log euro / leu ; dif leu / dleu
log pound / luk ; dif luk / dluk
log sw / lsw ; dif lsw / dlsw

* Create Figure 3.5 using:
labels pound sw euro;# 'Pound' 'Swiss Fr' 'Euro'
SPGRAPH
  gra(footer='Figure 3.5: Daily Exchange Rates (Jan 3, 2000 - April 4, 2013)', $
  vla='currency per dollar',patterns) 3
  # euro / 1 ; # pound / 2; # sw / 12
  GRTEXT(ENTRY=2000:6:1,Y=1.75,size=18) 'Pound'
  GRTEXT(ENTRY=2000:6:1,Y=1.05,size=18) 'Euro'
  GRTEXT(ENTRY=2000:6:1,Y=0.70,size=18) 'Sw. Franc'
SPGRAPH(DONE)
```

12. In Section 4, it was established that a reasonable model for the price of oil is an MA(1) with the GARCH conditional variance: $h_t = 0.402 + 0.097 \varepsilon_{t-1}^2 + 0.881h_{t-1}$.

Notes for EViews Users

1. In the Instructors' Manual, the workfile *aets4_ch3_q12.wfl* contains the spot price of oil and the variable $p = 100 * \text{dlog}(\text{spot})$. The time plot of *spot* is contained on *graphspot*.
2. The variable *dummy* was created using the second method discussed in Question 8 above. The variable *time* was generated using
`time = @trend+1`

Next, @recode was used to create the variable dummy using
dummy=@recode(time<1105,0,1)

3. The rest of the workfile is self-explanatory, The tabs are *p134*, *p135*, *p135b*, *part_a*, *part_b*, *part_c*, *part_d* and *part_f*. The EGARCH model is in *eq01*.

Sample Program for RATS Users

* Read in the data using

CAL(w) 1987 5 15

all 2013:11:1

open data c:\aets4\chapter_3\oil.xls

data(org=obs,format=xls)

set rate = 100.0*(log(spot)-log(spot{1}))

* Create Figure 3,6 with

gra(footer='Figure 3.6: Weekly Values of the Spot Price of Oil: (May 15, 1987 - Nov 1, \$
2013)',vla='dollars per barrel',patterns) 1

spot 2000:1:2 *

* To create Figure 3.13, standardize the sample data to mean zero, variance one.

diff(standardize) rate / stdreturn

density(smooth=1.5) stdreturn / xdensity fdensity

set normalf = %density(xdensity)

* Next is a t(3) standardized to a variance of 1.0. (The variance of

* non-standardized t(nu) is nu/(nu-2), which is 3 for nu=3).

set tf = %tdensity(xdensity*sqrt(3.0),3.0)*sqrt(3.0)

scatter(patterns,nokbox,footer="Figure 3.13 Distribution of Oil Price Changes",style=line, \$
key=below,klabels=||"Actual change","Normal density","t density"||) 3

xdensity fdensity

xdensity normalf

xdensity tf

CHAPTER 4

MODELS WITH TREND

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(Online in Supplementary Manual)
Appendix 4.1: The Bootstrap

Learning Objectives

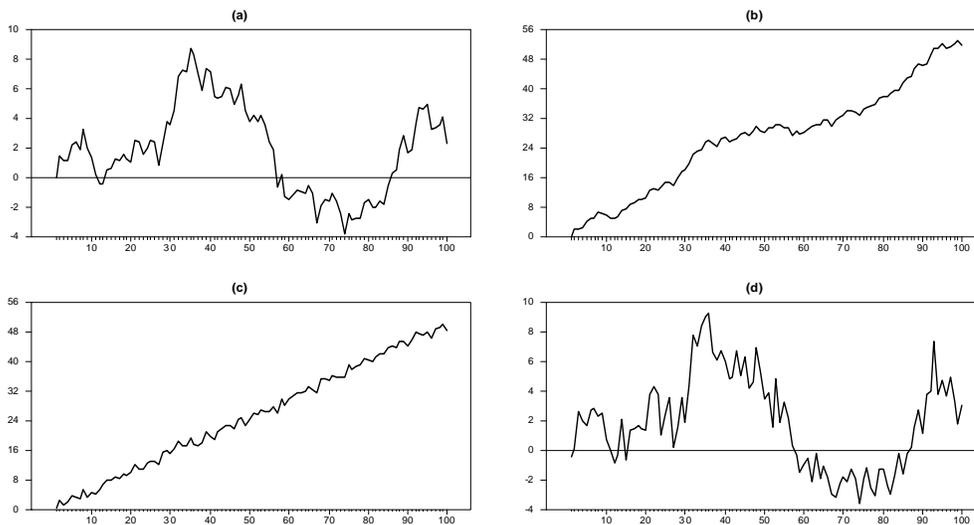
1. Formalize simple models of variables with a time-dependent mean.
2. Compare models with deterministic versus stochastic trends.
3. Show that the so-called unit root problem arises in standard regression and in times-series models.
4. Explain how Monte Carlo and simulation techniques can be used to derive critical values for hypothesis testing.
5. Develop and illustrate the Dickey–Fuller and augmented Dickey–Fuller tests for the presence of a unit root.
6. Apply the Dickey–Fuller tests to U.S. GDP and to real exchange rates
7. Show how to apply the Dickey–Fuller test to series with serial correlation, moving average terms, multiple unit roots, and seasonal unit roots.
8. Consider tests for unit roots in the presence of structural change.
9. Illustrate the lack of power of the standard Dickey–Fuller test.
10. Show that generalized least squares (GLS) detrending methods can enhance the power of the Dickey–Fuller tests
11. Explain how to use panel unit root tests in order to enhance the power of the Dickey–Fuller test.
12. Decompose a series with a trend into its stationary and trend components.

Lecture Suggestions

1. A common misconception is that it is possible to determine whether or not a series is stationary by visually inspecting the time path of the data. I try to dispel this notion using overhead transparencies of the four graphs in Figure 4.2. I cover-up the headings in figures and ask the students if they believe that the series are stationary. All agree that the two series in graph (b) and (c) of the figure 4.3 are non-stationary. However, there is no simple way to determine whether the series are trend stationary or difference stationary. I use these same overheads to explain why unit root tests have very low power. Figure 4.2 (with captions the captions removed) is reproduced on the next page for your convenience.

2. Much of the material in Chapter 4 relies on the material in Chapter 1. I remind students of the relationship between characteristic roots, stability, and stationarity. At this point, I solve some of the mathematical questions involving unit root process. You can select from Question 5, 6, 9 and 10 of Chapter 1 and Question 1 of Chapter 4.

Figure 4.3: Four Series With Trends



Selected Answers to Questions

4. Use the data sets that come with this text to perform the following:

- a. The file PANEL.XLS contains the real exchange rates used to generate the results reported in Table 4.8. Verify the lag lengths, the values of γ and the t -statistics reported in the left-hand-side of the table.
- b. Does the ERS test confirm the results you found in part a?

Notes for EViews Users

1. In the Instructors' Manual, the workfile *aets4_ch4_q4ab.wfl* contains the answers to parts a and b of this question. The file includes all of the exchange rate variables in PANEL.XLS and their logarithms. The log transformations are each preceded with an l and are followed by the country's initial. The raw data are in the file *panel.wfl*.
2. The table *df_a* contains the results of the Dickey-Fuller test for the log of the Australian exchange rate (*la*). Consider:

Null Hypothesis: LA has a unit root
 Exogenous: Constant
 Lag Length: 5 (Automatic - based on t-statistic, lagpval=0.1, maxlag=8)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-1.678217	0.4399
Test critical values:		
1% level	-3.482453	
5% level	-2.884291	
10% level	-2.578981	

Since the sample t -statistic is -1.678 and the 5% critical value is -2.88 , it is not possible to reject the null hypothesis of a unit root. Open the *la* series and select Unit Root Test from the View tab. For Test Type select Augmented Dickey-Fuller and in Test for a unit root in select the Level

button. Include an Intercept (not a Trend and Intercept). As can be seen from the output above, the Lag length was Automatic selection based on the t-statistic option using Maximum lags of 8.

3. In the Instructors' Manual, the results for the ERS test for the Australian and Canadian rates are in the Tables *ers_a* and *ers_c*. Again, open the *la* series and select Unit Root Test from the View tab. For Test Type select now select Dickey-Fuller GLS (ERS) and in Test for a unit root in select the Level button. Include an Intercept (not a Trend and Intercept).

4. In the Instructors' Manual, the workfile *aets4_ch4_q4c.wfl* contains the answers to part c of this question. The series *y*, *y_tilde*, *yd*, *z1* and *z2* are in the GROUP labeled *data*. You can examine *data* or the spreadsheet ERSTEXT.XLS to see how the data were generated. The results of the ERS test are in the Table *ers_test*.

Sample Program for RATS Users

```
*Read in the data set
cal 1980 1 4
open data c:\aets4\chapter_4\panel.xls
data(format=xls,org=obs)

dofor i = australia canada france germany japan netherlands uk us
    log i / lx
    @dfunit(method=gtos,maxlags=8,signif=0.05) lx
end dofor
```

- c. The file ERSTEST.XLS contains the data used in Section 10. Reproduce the results reported in the text. Instead of reading in the data, the following indicates how I generated the series:

Sample Program for RATS Users

```
all 200
seed 2009
set eps = %ran(1)
set(first=20.+eps(1)) y = 1 + 0.95*y{1} + eps

sou erstest.src ;* compile the procedure
@erstest y
```

- d. The file QUARTERLY.XLS contains the M1NSA series used to illustrate the test for seasonal unit roots. Make the appropriate data transformations and verify the results concerning seasonal unit roots presented in Section 7. The seasonal unit root procedures can be downloaded from the Estima website www.estima.com. HEGY.SRC performs the Hylleberg, Engle, Granger, and Yoo (HEGY) unit root test on quarterly data. MHEGY.SRC performs the test using monthly data.

ANSWER:

```
* Read in the data using:
cal(q) 1960 1
all 2012:4
open data c:\aets4\chapter_2\quarterly.xls
data(format=xls,org=obs)

set x = m1nsa
log x / lx
dif lx / dlx
source c:\winrats\hegyqnew.src
```

@hegyqnew(signif=0.05,criterion=nocrit,nlag=10) lx

5. The second column in the file BREAK.XLS contains the simulated data used in Section 8.
 - a. Plot the data to see if you can recognize the effects of the structural break.
 - b. Verify the results reported in Section 8.

Notes for EViews Users

1. The file *aets4_ch4_section 8.wfl* reproduces the results from Section 8. The graph of $y1$ is in the GRAPH *graph01*. In addition to the series $y1$ and $y2$, there are level shift and pulse dummy variables labeled dl and dp , respectively. To create dummy variables, you should see the discussion in Chapter 2, Question 16. For now, note the dummy variables can be generated using:

```
time = @trend(1)+1
dl = @recode(time>50,1,0)
dp = @recode(time=50,1,0)
```

In the Instructors' Manual, the ACF is in Table *acf_y1*; you can see that the series is quite persistent. A simple Dickey-Fuller test (ignoring the break) is in *df_y1* and the estimated model $y1_t = c + a_1y1_{t-1} + a_2time + a_3dl + a_4dp$ is in the Table *estimatedmodel_y1*.

2. The results for the series $y2$ are in similarly named Tabs.

RATS PROGRAM FOR PARTS A and B

The data set contains 100 simulated observations with a break occurring at $t = 51$. To replicate the results in section 8, perform the following:

```
all 100 ;* These three lines read in the data set
open data a:\break.xls
data(format=xls,org=obs)

set trend = t ;* Creates a time trend

* The graph of the series shown in Figure 4.10 was created using
graph 1 ;# y1

* The ACF is obtained using
cor(method=yule) y1
```

6. The file RGDP.XLS contains the real GDP data that was used to estimate (4.29).

Notes for EViews Users

1. In the Instructors' Manual, the workfile *aets4_ch4_q6.wfl* contains the answers to this question. In addition to the series in REAL.WF1, the file contains the log of real GDP (*lrgdp*), the growth rate of real GDP (*dlrgdp*). Note that *level* is a level shift dummy and *dtrend* is a dummy equal to zero until 1973Q1 and is equal to the series 105, 106, 107, ... thereafter. The dummies were created using a combination of the @recode, @data, @dateval, and @trend functions:

```
level = @recode(@date<@dateval("1973/02"), 1, 0)
dtrend = @recode(@date<@dateval("1973/02"), 0, @trend)
```

2. The Table *eq_429* reports the results of the Dickey-Fuller test reported on page 429 of the text and *perrontest* reports the results of the Perron test for *lrgdp*.

3. To obtain the results in *hpfilter* open the *lrgdp* series and select the PROC tab. In the OUTPUT series boxes, enter *hptrend* and *hpcycle* and do not change the default value of $\text{Lambda} = 1600$. The plot of *lrgdp*, *hptrend* and *hpcycle* are in the GRAPG *hpseries*.
4. The estimate for part *d* is in *part_d* and the residual plot are in *residuals_partd*.

Sample Program for RATS USERS

- a. The following program will replicate the results in Section 6.

READ IN THE DATA WITH

```
cal(q) 1947 1
all 2012:4
open data c:\aets4\real.xls
data(format=xls,org=obs)
```

* Transform the variables

```
set time = t
log rgdp / ly
dif ly / dly
```

```
lin dly ; # constant time ly{1} dly{1}
exclude ; # time ly{1}
exc ; # constant time ly{1}
```

You can create Figure 4.12 with

```
set trgdp = rgdp/1000. ; set trcons = rcons/1000. ; set trinv = rinvs/1000.
```

```
@hpfilter trgdp / hp_rgdp
@hpfilter trcons / hp_rcons
@hpfilter trinv / hp_rinv
```

```
spg(hfi=1,vfi=1)
```

```
gra(footer='Figure 4.12',pat,vla='trillions of 2005 dollars') 6
# trgdp / 2 ; # hp_rgdp / 1 ; # trcons / 2 ; # hp_rcons / 1 ; # trinv / 2 ; # hp_rinv
Grt(entry = 2003:1,y = 13,size=18) 'RGDP'
Grt(entry = 2004:1,y = 6.5,size=18) 'Consumption'
Grt(entry = 2004:1,y = 2.8,size=18) 'Investment'
```

```
spg(done)
```

7. The file PANEL.XLS contains the real exchange rate series used to perform the panel unit root tests reported in Section 11.
 - a. Replicate the results of Section 11.

Notes for EViews Users

1. In the Instructors' Manual, the answers are contained in the workfile *aets4_ch4_q7.wf1*. The first step is to group the log of the exchange rates as in the GROUP *groupedrates*. Go to the View tab and select Unit Root Test. In the dialogue box, for Test type select Individual root-Im, Pesaran, Shin. Select the Level button and include an Individual intercept.

SAMPLE RATS PROGRAM

Use the code in Question 4a to read in the data.

8. The file QUARTERLY.XLS contains the U.S. interest rate data used in Section 10 of Chapter 2. Form the spread, s_t , by subtracting the *t*-bill rate from the 5-year rate. Recall that the spread appeared to be quite persistent in that $\rho_1 =$

0.86 and $\rho_2 = 0.68$.

- a. One difficulty in performing a unit-root test is to select the proper lag length. Using a maximum of 12 lags, estimate models of the form $\Delta s_t = a_0 + \gamma s_{t-1} + \sum \beta_i \Delta s_{t-i}$. Use the AIC, BIC and general-to-specific (GTS) methods to select the appropriate lag length. You should find that the AIC, SBC and GTS methods select lag lengths of 9, 1, and 8, respectively. In this case, does the lag length matter for the Dickey-Fuller test?

Notes for EViews Users

1. In the Instructors' Manual, the workfile *aets4_ch4_q8.wfl* contains the answers to this question. Open the series *s* (= *r5* – *tbill*) and from the View tab select Unit Root Test. In the next dialogue box, for Test type, choose Augmented Dickey-Fuller and for Test for Unit Root in choose the Level button. Be sure to include only and intercept. In the Lag length section alternatively choose the AIC, SBC and t-statistic options.
2. If you enter 8 in the User specified box you will get the results for part *b*. The output is in the Table labeled *df_s*.
3. The Tables *df_r5* and *df_tbill* contain the results of the unit root test for *r5* and *tbill*.

Sample Program for RATS Users

READ IN THE QUARTERLY.XLS DATA SET AS ABOVE.

```
set s = r5 - tbill ; * form the spread
USE @DFUNIT to find the lag lengths using the three methods.
@dfunit(method=aic,signif=0.05,maxlags=12) s
@dfunit(method=bic,signif=0.05,maxlags=12) s
@dfunit(method=gtos,signif=0.05,maxlags=12) s
```

9. The file QUARTERLY.XLS contains the index of industrial production, the money supply as measured by M1, and the unemployment rate over the 1960Q1 to 2012Q4 period.

Notes for EViews Users

1. In the Instructors' Manual, the workfile *aets4_ch4_q9.wfl* contains the answers to all parts of this question. The file contains the variables *indprod*, *unemp* and *m1nsa*. The series *lindprod* = $\log(\text{indprod})$ is used for part *a*. The results of the Dickey-Fuller test for *lindprod* are contained in the Table labeled *part_a*.

Null Hypothesis: LINDPROD has a unit root
 Exogenous: Constant, Linear Trend
 Lag Length: 12 (Automatic - based on t-statistic, lagpval=0.1, maxlag=14)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-2.293050	0.435

- In order to reproduce these results, open the series *lindprod* and on the View menu select Unit Root Test. In the dialogue box Test type select Augmented Dickey-Fuller. Select the Level and Trend and intercept buttons. In the Lag length box, select t-statistic and use the default value of 14.
2. To use eight lagged changes for the *unemp* series, open the series and on the View menu select Unit Root Test. In the dialogue box Test type select Augmented Dickey-Fuller. Select the Level and intercept buttons. There is no reason to incorporate a trend for the unemployment rate series. In the Lag length box, select User specified and enter 8 in the dialogue box. You will obtain the results reported in the Table *part_b*.
 3. To use only one lagged change in the test, repeat the steps in part *b* but enter 1 in the dialogue box for Lag length. The result should be identical to that in the Table labeled *part_c*.
 4. The Table *part_d* reports the effects of regressing *indprod* on *m1nsa*. Note that the *t*-statistics are very high and

the R^2 is 0.86. The ACF of the residuals is reported in Table *part_d2*.

- a. Show that the results using this data set verify Dickey and Fuller's (1981) finding that industrial production (INDPROD) is $I(1)$. Use the log of INDPROD and select the lag length using the general-to-specific method.

Sample Program for RATS Users:

READ IN THE QUARTERLY.XLS DATA SET AS ABOVE.

```
log indprod / lx
@dfunit(method=gto,signif=0.05,maxlags=12,det=trend) lx
```

- b. Perform an augmented Dickey-Fuller test on the unemployment rate (UNEMP). If you use eight lagged changes you will find: $\Delta unemp_t = 0.181 - 0.029unemp_{t-1} + \sum \beta_i \Delta unemp_{t-i}$

$$(2.30) \quad (-2.25)$$

```
@dfunit(method=gto,signif=0.05,maxlags=12) unemp
```

10. Use the data in the file QUARTERLY.XLS to perform the following:

- a. Perform the DFGLS test using 1 lagged change of the log of INDPROD. You should find that the coefficient on γ is -2.04 . (Be sure to include a time trend.)

EViews Users

Open the workfile *aets4_ch4_q10.wfl* and click on the Table *part_a*. In order to reproduce these results, open the series *lindprod* and on the View menu select *Unit Root Test*. In the dialogue box *Test type* select *Dickey-Fuller GLS (ERS)*. Select the *Level* and *Trend* and *intercept* buttons. In the *Lag length* box, select *User specified* and enter 1 in the dialogue box.

RATS Users

```
log indprod / lx
@ERSTEST(DET=TREND,LAGS=1) LX
```

- b. Perform the DFGLS test using 8 lags of the change in UNEMP. You should find that the coefficient on γ is -1.83 .

EViews Users

To obtain the results in *part_b* open the series *unemp* and on the View menu select *Unit Root Test*. In the dialogue box *Test type* select *Dickey-Fuller SLS (ERS)*. Select the *Level* and *Intercept* buttons. In the *Lag length* box, select *User specified* and enter 8 in the dialogue box.

RATS Users

```
@ERSTEST(LAGS=8) unemp
```

- c. The SBC indicates that only one lagged change of UNEMP is appropriate. Now perform the DFGLS test using 1 lagged change of UNEMP. In what important sense is your answer quite different from that found in part b?

EViews Users

To obtain the results in *part_c* repeat the steps indicated in *part_b* above. However, in the *User specified* dialogue box enter 1.

RATS Users

```
@ERSTEST(LAGS=1) unemp
```

The series appears to be stationary with 1 lag but not with 8 lags.

11. Chapter 6 of the *Programming Manual* analyzes the real GDP data in the file QUARTERLY(2012).XLS. Unlike the real GDP data used in the text, the date in this file begins in 1960Q1. Perform parts a through e below using this shorter data set.

Notes for EViews Users

1. In the Instructors' Manual, the workfile *aets4_ch4_q11.wfl* contains the answers to all parts of this question. From the Quick tab, estimate the equation: `lrgdp c @trend`. This equation is labeled *eq_parta*. From the Proc menu, select `Make residual series` and name them *resid01*. In the workfile, we obtained the ACF of *resid01* and named them *part_a*. The correlations show only a mild tendency to decay.
2. Perform a Dickey-Fuller test on *lrgdp*. If you use the AIC to select the lag length, you should obtain the results in *part_b*:

Null Hypothesis: LRGDP has a unit root		
Exogenous: Constant, Linear Trend		
Lag Length: 2 (Automatic - based on AIC, maxlag=14)		
	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-2.163125982	0.50718420

3. Generate the series *cycle* as $\log(\text{potent}) - \text{lrgdp}$. Perform a unit root test (without a trend). The results are in *df_cycle* and the results are in *gls_cycle*. Note that the DF-GLS test is more supportive of stationarity than the DF test.

Selected Program for RATS Users

- a. Form the log of real GDP as $ly_t = \log(\text{RGDP})$. Detrend the data with a linear time trend and form the autocorrelations.

ANSWER:

```
*READ IN THE DATA USING:
cal(q) 1960 1
all 2012:4
open data c:\RatsManual\quarterly(2012).xls
data(org=obs,format=xls)

log rgdp / ly
set trend = t
lin ly / resid1 ; # constant trend
cor(number=8,picture='###.##') resid1
```

CHAPTER 5

MULTIEQUATION TIME-SERIES MODELS

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Learning Objectives

1. Introduce intervention analysis and transfer function analysis.
2. Show that transfer function analysis can be a very effective tool for forecasting and hypothesis testing when it is known that there is no feedback from the dependent to the so-called independent variable.
3. Use data involving terrorism and tourism in Italy to explain the appropriate way to estimate an autoregressive distributed lag (ADL).
4. Explain why the major limitation of transfer function and ADL models is that many economic systems do exhibit feedback.
5. Introduce the concept of a vector autoregression (VAR).
6. Show how to estimate a VAR. Explain why a structural VAR is not identified from a VAR in standard form.
7. Show how to obtain impulse response and variance decompositions.
8. Explain how to test for lag lengths, Granger causality, and exogeneity in a VAR.
9. Illustrate the process of estimating a VAR and for obtaining the impulse responses using transnational and domestic terrorism data.
10. Develop two new techniques, structural VARs and multivariate decompositions, which blend economic theory and multiple time-series analysis.
11. Illustrate several types of restrictions that can be used to identify a structural VAR.
12. Show how to test overidentifying restrictions. The method is illustrated using both macroeconomic and agricultural data.
13. Explain how the Blanchard–Quah restriction of long-run neutrality can be used to identify a VAR.

14. The Blanchard–Quah decomposition is illustrated using real and nominal exchange rates.

Key Concepts

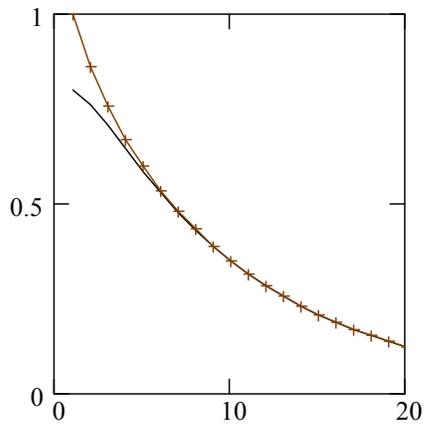
1. Although it is possible to skip the estimation of transfer functions, Sections 1 through 3 act as an introduction to VAR analysis. In a sense, VAR analysis can be viewed as a progression. Intervention analysis treats $\{y_t\}$ as stochastic and $\{z_t\}$ as a deterministic process. Transfer function allows $\{z_t\}$ to be stochastic, but assumes that there is no feedback from the $\{y_t\}$ sequence to the $\{z_t\}$ sequence. The notion of an autoregressive distributed lag (ADL) is also introduced here. Finally, VAR analysis treats all variables symmetrically. In my classes I use Section 4 to explain the limitations of intervention and transfer function analysis and to justify Sims' methodology.

2. I emphasize the distinction between the VAR residuals and the structural innovations. Questions 4, 5, and 6 at the end of the chapter are especially important. I work through one of these questions in the classroom and assign the other two for homework. You might project Figure 5.7 in order to illustrate the effects of alternative orderings in a Choleski decomposition. A large-sized version of the figure is included here for your convenience.

Figure 5.7: Two Impulse Response Functions

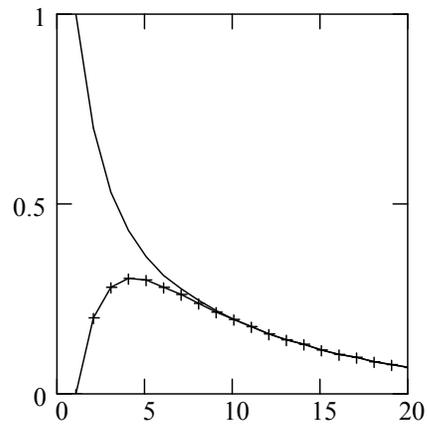
$$\text{Model 1: } \begin{pmatrix} y_t \\ z_t \end{pmatrix} = \begin{pmatrix} 0.7 & 0.2 \\ 0.2 & 0.7 \end{pmatrix} \begin{pmatrix} y_{t-1} \\ z_{t-1} \end{pmatrix} + \begin{pmatrix} u_t \\ v_t \end{pmatrix}$$

Response to ε_{zt} shock



(a)

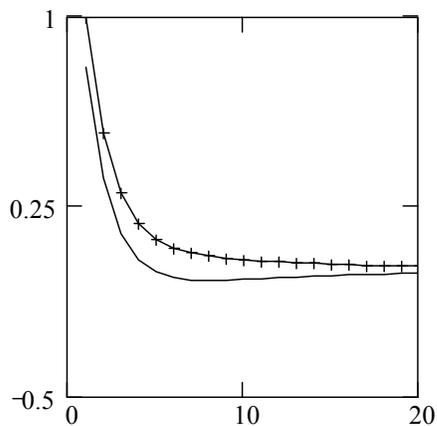
Response to ε_{yt} shock



(b)

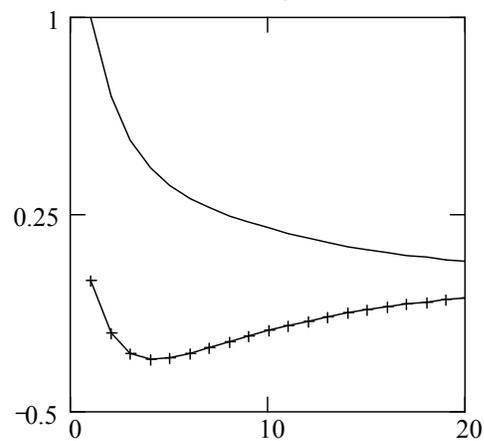
$$\text{Model 2: } \begin{pmatrix} y_t \\ z_t \end{pmatrix} = \begin{pmatrix} 0.7 & -0.2 \\ -0.2 & 0.7 \end{pmatrix} \begin{pmatrix} y_{t-1} \\ z_{t-1} \end{pmatrix} + \begin{pmatrix} u_t \\ v_t \end{pmatrix}$$

Response to ε_{zt} shock



(c)

Response to ε_{yt} shock



(d)

Legend: Solid line = $\{y_t\}$ sequence Cross-hatch = $\{z_t\}$ sequence

Note: In all cases $u_t = 0.8v_t + \varepsilon_{yt}$ and $v_t = \varepsilon_{zt}$

Selected Answers to Questions

2. The data set TERRORISM.XLS contains the quarterly values of various types of domestic and terrorist incidents over the 1970Q1–2010Q4 period.

Notes for EViews Users

1. In the Instructors' Manual, the workfile *aets4_ch5_q2.wfl* contains the domestic and transnational terrorism series. The Table *acf_trans_to1997q4* contains the ACF of the transnational terrorism series through 1997Q4. Notice that the ACF decays after lag 2 ($\rho_2 > \rho_1$) and the PACF cuts to zero beyond lag 2.
2. The dummy variable *soviet* was created using

```
dummy = @recode(@date>@dateval("1997/04"), 1, 0)
```

The two models Jennifer estimated are reported in the Tables *partb_eq1* and *partb_eq2*.
3. The ACF and PAF for the entire period are in the Table *partc*. Note the slow decay of the ACF. This could induce Justin to conclude that the series is very persistent. Justin's model is reported in the Table *partd*.
4. The second dummy (*d2*) was created using

```
d2 = @recode(@date>@dateval("1991/04"), 1, 0)
```

Justin's model using both dummy variables are in *parte*.

Sample Program for RATS Users

* Read in the data using

```
cal(q) 1970:1  
OPEN DATA "C:\TERRORISM.XLS"  
DATA(FORMAT=XLS,ORG=COLUMNS)
```

* Figure 5.1 was created using

```
spg(hfi=1,vfi=2,footer='Figure 5.1 Domestic and Transnational Terrorism')  
  gra(Hea='Panel (a): Domestic Incidents',vla='incidents per quarter') 1 ; # Domestic  
  gra(Hea='Panel (b): Transnational Incidents',vla='incidents per quarter') 1 ; # transnational  
spg(done)
```

b. To obtain Jennifer's two results create the dummy variable *soviet* and estimate the following two regressions.

```
set soviet = %if(t>1997:4,1,0)  
lin y / resids ; # constant soviet ; * ( soviet = z )  
lin y / resids ; # constant y{1 2} soviet
```

c. As indicated in Chapter 4, an ignored structural break can make a series appear to be a unit root process.

d. Obtain Justin's results using

```
BOXJENK(REGRESSORS,CONST,AR=1,MA=1) Y  
# SOVIET
```

e. To use both a pulse and a level shift dummy, use:

```
set d2= %if(t.eq.1991:4,1,0)  
lin y / resids ; # constant y{1 2} soviet d2
```

5. Use the data on the file ITALY.XLS to estimate a model in the form of (5.9) using $p = n = 6$.

Notes for EViews Users

1. The workfile *italy.wfl* contains the variables *slitlay* and *atkit*.
2. In addition to the estimates pertaining to the question, in the Instructors' Manual the workfile contains the results

reported in Section 3. Specifically:

The Table `basicad1` contains the estimated model using six lags of each variable.

The F -test results for the sixth lag of each variable are in the Table `table01f_test`.

The cross correlaogram, the estimate of equation 5.15, model 3, the pared down model, and the residual autocorrelation are in the appropriately labeled files.

For RATS users, the key results in the text can be obtained using the program

* Read in the data set

```
open data italy.xls
calendar(q) 1971:1
data(format=xls,org=columns) 1971:01 1988:04 entry slitaly attkit
```

* Obtain the cross correlations

```
CROSS(FROM=0,TO=12,pict='###.##') SLITALY ATTKIT
```

* Estimate the ADL with 6 lags of each variable

```
lin slitaly ; # constant slitaly{1 to 6} attkit{0 to 6}
```

9. This set of exercises uses data from the file entitled QUARTERLY.XLS in order to estimate the dynamic interrelationships among the level of industrial production, the unemployment rate, and interest rates. In Chapter 2, you created the interest rate spread (s_t) as the difference between the 10-year rate and the T -bill rate. Now, create the logarithmic change in the index of industrial production ($indprod$) as $\Delta lip_t = \ln(indprod_t) - \ln(indprod_{t-1})$ and the difference in the unemployment rate as $\Delta ur_t = unemp_t - unemp_{t-1}$.

Notes for Eviews Users

1. The workfile `aets4_ch5_q910.wf1` contains the variables `tbill`, `r5`, `unemp` and `indprod`. The spread was generated using $s = r5 - tbill$, the growth rate of industrial production is $dlip = \log(indprod) - \log(indprod(-1))$, and the change in the unemployment rate is $dur = unemp - unemp(-1)$.
2. The three variable VAR with 9 lags is in the Table `var_9lags` and the 3-lag model is in the Table `var_3lags`.
3. The SYSTEM `varmodel` allows you to perform the various lag length tests. The Estimate tab allows you to change the lag lengths. Form the estimated model select the View tab and them select the Lag Structure option. The Lag Exclusion Tests option will perform Wald tests for the alternative lag lengths and the Lag Length Criteria option will produce the various lag length selection criteria. For example, for the 9-lag model, this selection yields the Table `lagcriteria`:

VAR Lag Order Selection Criteria
 Endogenous variables: DLIP DUR S
 Exogenous variables: C
 Date: 08/06/14 Time: 14:38
 Sample: 1960Q1 2012Q4
 Included observations: 202

Lag	LogL	LR	FPE	AIC	SC	HQ
0	324.9193	NA	8.29e-06	-3.187320	-3.138187	-3.167441
1	544.0122	429.5088	1.04e-06	-5.267448	-5.070917*	-5.187931*
2	552.4162	16.22544	1.04e-06	-5.261546	-4.917617	-5.122392
3	565.7126	25.27636	9.98e-07	-5.304085	-4.812758	-5.105293
4	572.8451	13.34702	1.02e-06	-5.285595	-4.646870	-5.027166
5	579.6017	12.44282	1.04e-06	-5.263383	-4.477260	-4.945316
6	591.1367	20.89999	1.02e-06	-5.288482	-4.354961	-4.910778

7	604.1574	23.20527	9.76e-07*	-5.328291	-4.247372	-4.890949
8	611.7356	13.28055	9.92e-07	-5.314214	-4.085896	-4.817234
9	622.3190	18.23280*	9.78e-07	-5.329891*	-3.954176	-4.773274

Program for RATS Users

* Read in the data using:

```
cal(q) 1960 1
all 2012:4
open data c:\aets4\chapter_2\quarterly.xls
data(format=xls,org=obs)
```

```
* Create the three variables
set s = r5 - tbill
set dur = unemp - unemp{1}
set dlip = log(indprod)-log(indprod{1})
```

```
* Estimate the VAR with 9 lags
system(model=chap5)
var dlip dur s
lags 1 to 9
det constant
end(system)
estimate(residuals=resids9)
```

10. Question 9 indicates that a 3-lag VAR seems reasonable for the variables Δlip_t , Δur_t , and s_t . Estimate the three-
VAR beginning in 1961Q1 and use the ordering such that Δlip_t is causally prior to Δur_t and that Δur_t is causally prior
to s_t .

Notes for EViews Users

1. In the Instructors' Manual, the workfile *aets4_ch5_q910.wf1* continues with the answers to question 10. The SYSTEM var3lags contains the estimates of the 3-lag VAR. To obtain this result select Estimate VAR from the Quick menu. Be sure to enter the variables in the order *dlip*, *dur* and *s*.
2. Click the SYSTEM var3lags, choose the View tab on the Lag Structure tab and then select Granger Causality/Block Exogeneity. You should obtain the Table q10_parta:

VAR Granger Causality/Block Exogeneity Wald Tests
Date: 08/06/14 Time: 14:51
Sample: 1960Q1 2012Q4
Included observations: 208
Dependent variable: DLIP

Excluded	Chi-sq	df	Prob.
DUR	4.727485	3	0.1929
S	7.326044	3	0.0622
All	13.08164	6	0.0418

Dependent variable: DUR

Excluded	Chi-sq	df	Prob.
DLIP	16.23776	3	0.0010
S	17.80474	3	0.0005
All	32.68401	6	0.0000

Dependent variable: S			
Excluded	Chi-sq	df	Prob.
DLIP	1.188741	3	0.7557
DUR	4.423043	3	0.2193
All	17.33896	6	0.0081

3. The selection `Impulse` will yield the impulse response function (see the Table `impulseresponses`). The variance decompositions are in the Table `variancedecompositions`.

Sample Program for RATS Users

a. If you perform a test to determine whether s_t Granger causes Δlip_t , you should find that the F -statistic is 2.44 with a $prob$ -value of 0.065. How do you interpret this result?

```
* Continue with the program above. Note that the Granger-causality tests are produced with: system(model=chap5)
var dlip dur s
lags 1 to 3
det constant
end(system)
estimate(residuals=resids3,out=sigma)
```

11. This set of exercises uses data from the file entitled `QUARTERLY.XLS` in order to estimate the dynamic effects of aggregate demand and supply shocks on industrial production and the inflation rate. Create the logarithmic change in the index of industrial production ($indprod$) as $\Delta lip_t = \ln(indprod_t) - \ln(indprod_{t-1})$ and the inflation rate (as measured by the CPI) as $inf_t = \log(cpi_t) - \log(cpi_{t-1})$.

Notes for EViews Users

- The workfile `aets4_ch5_q11.wfl` contains the variables `cpi` and `indprod`. The variables `inf` and `dlip` were generated as:

$$inf = \log(cpi) - \log(cpi(-1)) \text{ and } dlip = \log(indprod) - \log(indprod(-1)).$$
- The unit root tests are in the Tables `parta_a` and `partb_b`. To reproduce the results for `dlip`, open the series `dlip` and select `Unit Root Test` from the `View` tab. It should be clear that the variable is stationary. However, the results for `inf` are not as straightforward. If you select the `AIC` or `SBC` from the `Lag length` dialogue box, it is just possible to reject the null at the 5% level. However, if you use the `general-to-specific` method (i.e., the `t-statistic` option), it is not possible to reject the null of a unit root at conventional significance levels.
- The Table `var_3lags` contains the results for the 3-lag model. The residuals are in the series `resid01` and `resid02`. To perform the Granger causality tests, click the `SYSTEM` `bq_var`, choose the `View` tab on the `Lag Structure` tab and then select `Pairwise Granger Causality`, you should obtain the results in the Table `grangercausality`.
- The impulse responses are in the
- As described in the EViews manual, in order to perform the BQ decomposition it is necessary to construct the pattern matrix

	NA	NA
0.000000		NA

This is `patc` in the workfile. You can create this matrix with the following commands:

```
matrix(2,2) patc = na
patc(2,1) = 0
```

Now select `Proc/Estimate Structural Factorization` from the `VAR` tab. Next, click `Matrix` and in the `SVAR` dialogue box choose `Long-Run Pattern` and enter `patc`. You should obtain the results in the `bq_martix` and `bq_impulseresponses` tables.

Sample Program for RATS USERS

a. Determine whether Δlip_t and inf_t are stationary.

*Perform the unit root tests with

```
set dlip = log(indprod)-log(indprod{1})
```

```
set inf = log(cpi) - log(cpi{1})
```

```
@dfunit(method=gotos,signif=0.05,maxlags=12) inf
```

```
@dfunit(method=gotos,signif=0.05,maxlags=12) dlip
```

CHAPTER 6: COINTEGRATION AND ERROR-CORRECTION MODELS

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Online material in Supplementary Manual

Appendix 6.1: Characteristic Roots, Stability, and Rank

Appendix 6.2: Inference on a Cointegrating Vector

Learning Objectives

1. Introduce the basic concept of cointegration and show that it applies in a variety of economic models
2. Show that cointegration necessitates that the stochastic trends of nonstationary variables be linked.
3. Consider the dynamic paths of cointegrated variables. Since the trends of the variables are linked, the dynamic paths of such variables must respond to the current deviation from the equilibrium relationship.
4. Develop the Engle–Granger cointegration test. The econometric methods underlying the test procedures stem from the theory of simultaneous difference equations.
5. The Engle–Granger method is illustrated using simulated data.
6. Illustrate the Engle–Granger method using real exchange rate data.
7. Develop the Johansen full-information maximum likelihood cointegration test.
8. Show how to test restrictions on cointegrating vectors. Discuss inference in models with $I(1)$ and $I(2)$ variables.
9. Illustrate the Johansen test using simulated data.
10. Show how to estimate ADL models using nonstationary variables and develop the ADL cointegration test.
11. Compare the Engle–Granger, Johansen, and ADL cointegration tests using interest rate data.

Key Concepts

Figure 6.1 and Worksheet 6.1 illustrate the concept of cointegration. Worksheet 6.2 illustrates spurious regressions. You can use Figures M6-1 and M6-2 below for further emphasis. The first two panels in Figure M6-1 show 100 realizations of two independent unit root processes. The $\{y_t\}$ and $\{z_t\}$ sequences were constructed as:

$$y_t = 0.1 + y_{t-1} + \varepsilon_{yt}$$

and:

$$z_t = 0.2 + z_{t-1} + \varepsilon_{zt}$$

where: ε_{yt} and ε_{zt} are independent white-noise disturbances.

Two sets of one hundred random numbers were drawn to represent the $\{\varepsilon_{yt}\}$ and $\{\varepsilon_{zt}\}$ sequences. Using the initial values $y_0 = 0$ and $z_0 = -5$, the next 100 realizations of each were constructed using the formulas above. The drift terms impart a positive trend to each. Since each sequence tends to increase over time, the two appear to move together. The scatter plot in the third panel and the time plots in the fourth panel reflect this tendency. The spurious regression of y_t on z_t appears to have a "good" fit. However, regression coefficients are meaningless. The problem is that the error-term is a unit-root process; all deviations from the regression line are permanent.

In contrast, the simulated $\{y_t\}$ and $\{z_t\}$ sequences shown in Figure M6-2 are cointegrated. The two random-walk plus noise processes were simulated as:

$$\begin{aligned} y_t &= y_{t-1} + \varepsilon_t + \eta_{yt} - \eta_{yt-1} \\ z_t &= z_{t-1} + \varepsilon_t + \eta_{zt} - \eta_{zt-1} \end{aligned}$$

where: ε_t , η_{yt} , and η_{zt} are computer generated random numbers.

The series have the same stochastic trend. The scatter plot in the third panel and the time plots in the fourth panel reflect the tendency of both to rise and fall together in response to the common $\{\varepsilon_t\}$ shocks. The regression of y_t on z_t yields a stationary error process. Hence, all deviations from the regression line are temporary.

Notes for EViews Users

1. In the Instructors' Manual, the workfiles *aets4_ch6_figure62.wfl* and *aets4_ch6_figure63.wfl* were used to construct Figures 6.2 and 6.3. Notice that you can open the files to examine how the various series were constructed. You can also examine the files used to create the two worksheets. These two files are named *aets4_ch6_worksheet61.wfl* and *aets4_ch6_worksheet62.wfl*.
2. EViews reports the results of error correction models differently than other software packages. In RATS, for example, error correction models are estimated using the two-step Engle-Granger procedure. As such, the error correction term is the residual from the long-run relationship. In EVIEWS, the estimated model uses a one-step method maximum likelihood estimator. Thus the results can differ from those reported in the text.

As illustrated below, in EVIEWS you can select an error correction model from the Quick tab. Select Estimate VAR from the Quick menu. In VAR Specification, select Vector Error Correction. If, for example, you estimate an error correction model for y_t and z_t without any deterministic regressors and 1 lag of each variable, the output will be in the form:

y(-1)	1.000000	
z(-1)	β_1	
Error Correction:	DY	DZ
CointEq1	α_1	α_2
D(Y(-1))	γ_{11}	γ_{21}
D(Z(-1))	γ_{12}	γ_{22}

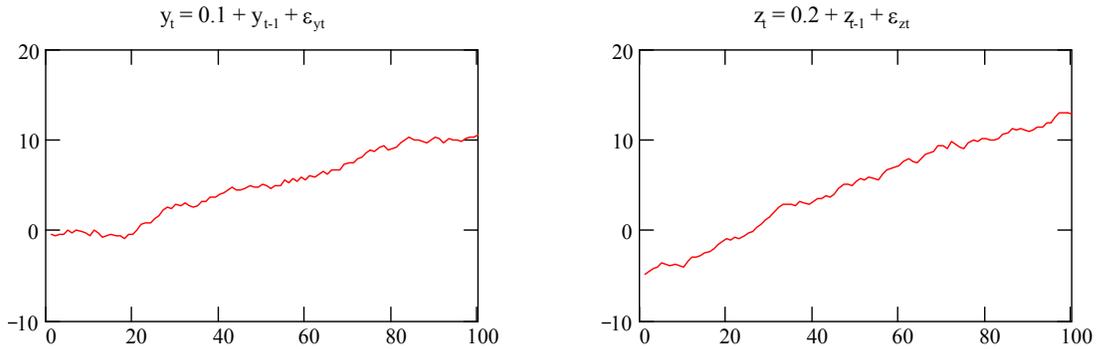
The estimated model is:

$$\Delta y_t = \alpha_1(y_{t-1} + \beta_1 z_{t-1}) + \gamma_{11} \Delta y_{t-1} + \gamma_{12} \Delta z_{t-1} + \varepsilon_{1t}$$

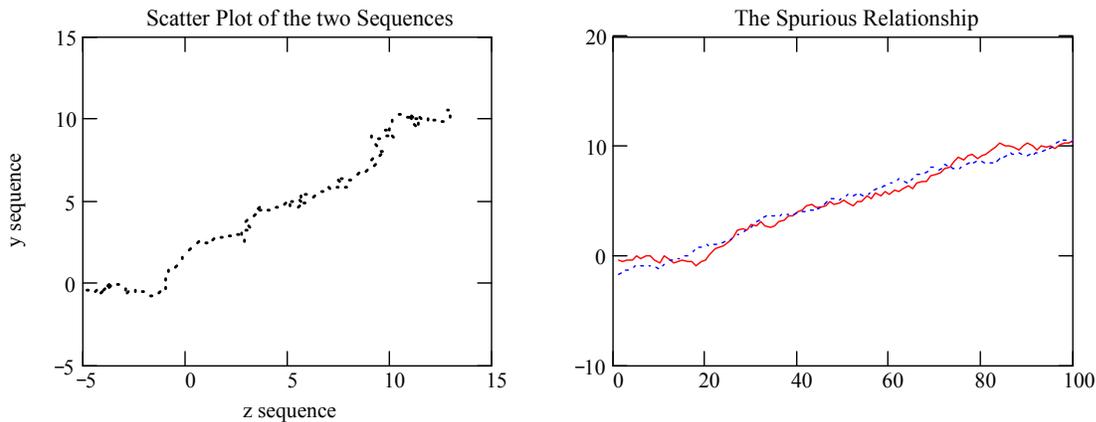
$$\Delta z_t = \alpha_2(y_{t-1} + \beta_1 z_{t-1}) + \gamma_{21} \Delta y_{t-1} + \gamma_{22} \Delta z_{t-1} + \varepsilon_{2t}$$

The error correction term $y_{t-1} + \beta_1 z_{t-1}$ and the speed of adjustment coefficients are estimated using full information maximum likelihood methods (as in the Johansen Procedure).

Figure M6-1: A Spurious Regression

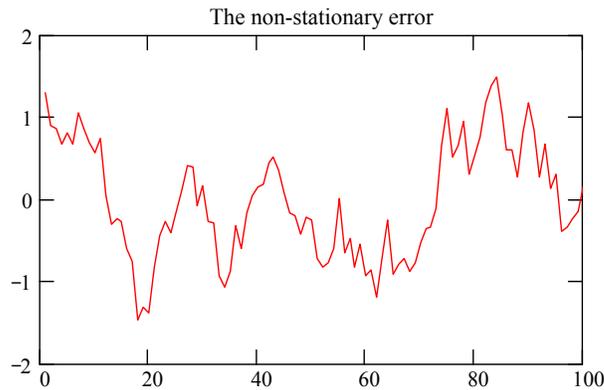


Both sequences were simulated as independent unit root processes. Each has a positive drift so that the two sequences tend to increase over time. The relationship is spurious.



The scatter plot captures the tendency of both series to increase over time. The regression of y on z yields: $y = 0.68z + 1.63$.

Transform the z sequence as: $w = 0.68z + 1.63$. The time paths of y and w seem to move together. However, the regression coefficients are meaningless.

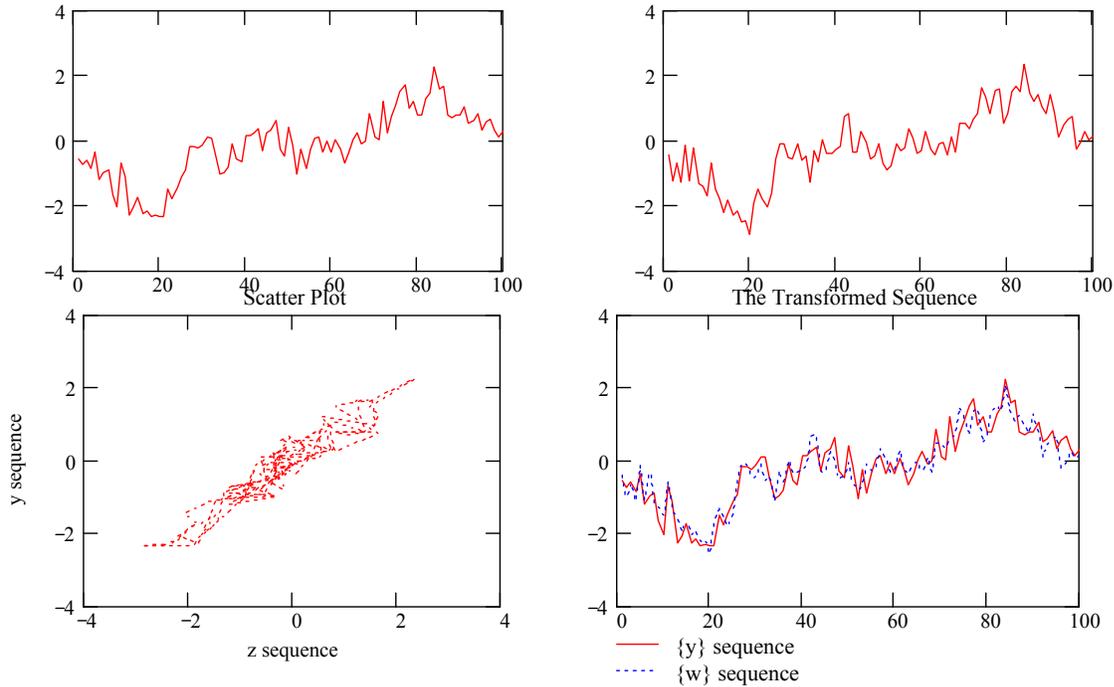


The regression error-term $y - 0.68z - 1.63$ is non-stationary. Hence, all deviations from the estimated relationship are permanent; the regression is spurious.

Figure M6-2: An Equilibrium Relationship

$$y_t = y_{t-1} + \varepsilon_{yt}$$

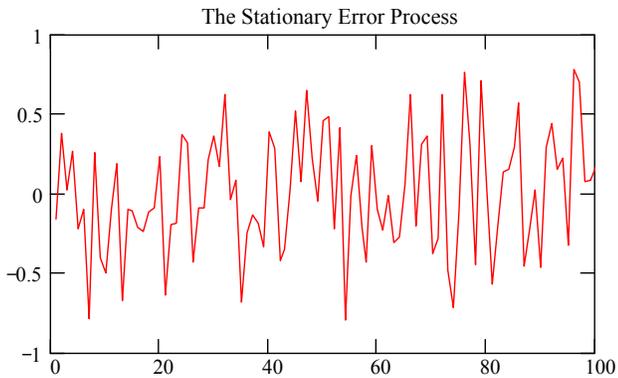
$$z_t = z_{t-1} + \varepsilon_{zt}$$



The simulated $\{y_t\}$ and $\{z_t\}$ sequences are both random-walk plus noise processes. Each meanders without any tendency to return to a long-run mean value. The error terms are: $\varepsilon_{yt} = \varepsilon_t + \eta_{yt} - \eta_{yt-1}$ and $\varepsilon_{zt} = \varepsilon_t + \eta_{zt} - \eta_{zt-1}$. Since each has the same stochastic trend, the $\{y_t\}$ and $\{z_t\}$ series are cointegrated.

The scatter plot of z_t and y_t captures the tendency of both series to move together. The regression of y_t on z_t yields: $y_t = 0.889z_t + 0.007$.

Transform the z_t sequence as: $w_t = 0.889z_t + 0.007$. The time paths of y_t and w_t move together as a result of the common stochastic trend.



The regression error-term $y_t - 0.889z_t - 0.007$ is stationary. Hence, all deviations from the estimated relationship are temporary. The variables are cointegrated

Selected Answers to Questions

2. The data file **COINT6.XLS** contains the three simulated series used in sections 5 and 9. The following programs will reproduce the results.

Notes for EViews Users

1. In the Instructors' Manual, the workfile *aets4_ch6_q2a.wfl* contains the results for part a. The series *w*, *y*, and *z* contain the three variables of interest. The GRAPH figure_62 reproduces Figure 6.2 of the text. The TABLES *df_w*, *df_y*, and *df_z* report the unit root tests in Table 6.2. To reproduce the results, open a series and from the View tab select Unit Root Test. In the dialogue box, choose the Augmented Dickey-Fuller and for Lag length enter 4 in the User specified box.
2. To reproduce the results in TABLE *p379_y*, use Quick and Estimate Equation. Let *y* be the "dependent variable" and include an intercept, *z* and *w* in the regression. Next, select Proc and Make Residual Series to obtain the residuals from this regression. In the workfile, this series is called *resid_y*. Now, perform a unit root test on *resid_y*. Be sure that you do not include any deterministic regressors in the equation. You should find your results are consistent with those in *table63_y*. Repeat the exercise for the *z* and *w* series. The TABLE *p379_w* contains the results using *w* as the dependent variable and the residuals are in *resid_w*. The results if the Engle-Granger test are in *table63_w*.
3. The series *dy*, *dz*, and *dw* are the first-differences of *y*, *z* and *w*. To obtain the results in equation (6.37) *eq637*, use Quick Estimate Equation and enter
dy c resid_w(-1) dy(-1) dz(-1) dw(-1)
4. To reproduce the results in Section 9, select Estimate VAR from the Quick menu. In VAR Specification, select Vector Error Correction and use 1 lag (Note that this means that there is one lagged change). On the Cointegration tab use option 2 (constant in the cointegrating vector only). The results are in the TABLE *vec*.
5. Next, select the View tab and choose Cointegration test. The results are in *table6_6*.
6. The workfiles *aets4_ch6_figure62.wfl* and *aets4_ch6_figure63.wfl* contain the series used to construct Figures 6.2 and 6.3. Notice that you can open the files to examine how the various series were constructed.

Sample Program for RATS Users

all 100

open data c:\aets4\coint6.xls

data(format=xls,org=obs) / y z w

table ;* Produce summary statistics for y, z and w

dif y / dy ;* Take first-differences

dif z / dz

dif w / dw

linreg dy ;* Perform Dickey-Fuller test

constant y{1}

linreg dy ;* Perform Augmented Dickey-Fuller test

constant y{1} dy{1 to 4}

You can obtain the lag length for the VAR using one of the three selection criterion:

@varlagselect(lags=4,crit=gtos) ; # y z w

@varlagselect(lags=4,crit=aic) ; # y z w

@varlagselect(lags=4,crit=bic) ; # y z w

* To reproduce the results in Section 9, use the CATS procedure or use the file entitled *johmle.src*. Estimate the model

with a restricted constant:

```
@johmle(lags=2,det=rc)
# y z w
```

3. In Question 9 of Chapter 4 you were asked to use the data on QUARTERLY.XLS to estimate the regression equation

$$INDPROD_t = 30.48 + 0.04M1NSA_t \\ (29.90) \quad (36.58)$$

a. Use the Engle–Granger test to show that the regression is spurious.

Notes for EViews Users

1. In the Instructors' Manual, the workfile *aets4_ch6_q3ab.wfl* contains the answers to parts a and b. The file contains the series *indprod* and *m1nsa*. Use **Quick and Estimate Regression** to estimate the desired regression; enter

```
indprod c m1nsa
```

to obtain the results reported in the TABLE *regression_parta*.

From the **Proc** tab select **Make Residual Series** and call the residuals *resids_parta*. Open this residual series and select **Unit Root Test** from the **View** tab. The TABLE *engle_grangerparta* contains the results.

2. The scatter plot of the two series is contained in the GRAPH *partb*.

3. The workfile *aets4_ch6_q3c.wfl* contains the answers to part c. The logs of *rgdp* and *rcons* are called *ly* and *lc*, respectively. Use **Quick and Estimate Regression** to estimate the desired regression

```
lc c ly
```

The results are in the TABLE *regression_3c*. Use the instructions above to make the residual series (called *resid01*) that are reported in the TABLE *residuals*. The TABLE *engle_granger* contains the desired test statistics. To reproduce the results, open *resid01*, and from the **View** tab select **Unit Root Test**. Do not include any deterministic regressors.

Sample Program for RATS Users

*Read in the data set using:

```
cal(q) 1960 1
all 2012:4
open data c:\aets4\quarterly.xls
data(format=xls,org=obs)
```

* You can obtain the regression result using

```
lin indprod / resids ; # constant m1nsa
```

* Perform the Engle-Granger test using

```
dif resids / dresids
lin dresids ; # resids{1} dresids{1 to 3}
```

4. The file labeled QUARTERLY.XLS contains the interest rates paid on U.S. 3-month, 5-year, and 10-year U.S. government securities. The data run from 1960Q1 to 2012Q4. The variables are labeled TBILL, R5, and R10, respectively.

Notes for EViews Users

1. In the Instructors' Manual, the workfile *aets4_ch6_q4.wfl* contains the variables *tbill*, *r5* and *r10*. The TABLE *parta_tbill* contains the results of the Dickey-Fuller test for *tbill*. To reproduce the results, open *tbill* and from the **View** tab select **Unit Root Test**. In the dialogue box, choose the **Augmented Dickey-Fuller** and for **Lag length** select **t-statistic** with a **Maximum Lags** of 8. Repeat for the other rates.

- Use `Quick and Estimate Regression` to estimate the desired regression; enter `tbill c r5 r10` to obtain the results reported in the TABLE *partb*.

From the `Proc` tab select `Make Residual Series` and call the residuals *residuals*. Open this residual series and select `Unit Root Test` from the `View` tab. The TABLE *partb_englegranger* contains the results. For part c of the question, repeat using the other interest rates as the dependent variables. For example the TABLE *partc* uses *r10* as the dependent variable, the residuals are called *residuals_partc* and the results of the test are in the TABLE *partc_englegranger*.

- The TABLE *vec* contains the estimated error correction model. Open the `GROUP var` to see how the results were obtained. Select the `View` tab, select `Cointegration test` and select button 2 (`Intercept (no trend)` in `CE - no intercept in VAR`). The lag interval should be 1 7. You should obtain the results reported in the TABLE *partd*.

Sample Program for RATS Users

* Read in the data set using the first 4 lines from Question 3. Next perform the unit root tests using `dfunit.src`
`@dfunit(maxlags=8,method=gtos,signif=0.05) tbill`

* Estimate the long run relationship using:
`linreg(define=rshort) tbill / resid1`
`# constant r5 r10`

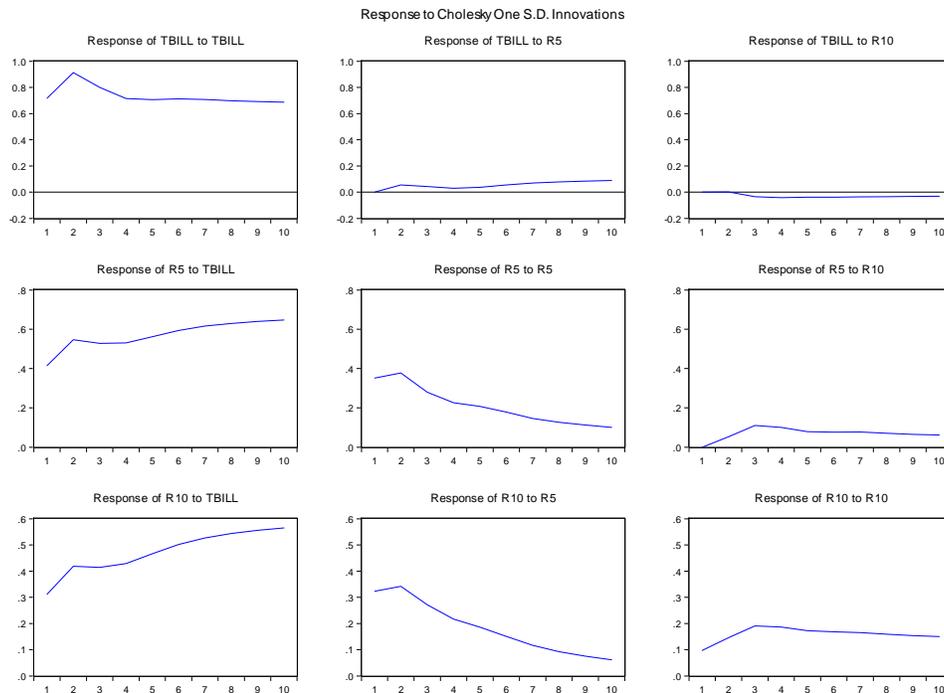
* Compile `johmle.src` and then enter the commands:
`@johmle(lags=8,determ=rc)`
`# tbill r5 r10`

5. In Question 4, the Engle–Granger methodology found that the long-run equilibrium relationship for the three interest rates was

$$TBILL_t = 0.367 - 1.91R5_t + 2.74 R10_t$$

Notes for EViews Users

- In the Instructors' Manual, the workfile `aets4_ch6_q5.wfl` continues with the results of Question 4. Recall that the TABLE *vec* contains the error-correction model. To proceed with the question, open `var01` and from the `Estimate` tab select button 2 in `VAR Type`, enter the `Endogenous Variables` in the order `tbill r5 r10` and use only 2 lagged changes—the results are in `var01`. Be sure to select button 2 (`Vector Error Correction`) in the `VAR Type` dialogue box. Now select the `Cointegration` tab and select button 2. The estimated model is in the TABLE *parta*.
- From `var01`, select the `Impulse` tab. If you use the defaults you will obtain the graph in *partb*:



3. To obtain the variance decompositions, from *var01*, select **Variance Decompositions** from the **View** tab. The results are in *partc*.

Sample Program for RATS Users

* Find the appropriate lag length for the VAR with:

```
@varlagselect(crit=aic,signif=0.05,lags=8) ; # tbill r5 r10
```

* Estimate the error correcting model using:

```
system(model=q4)
variables tbill r5 r10
lags 1 to 3
*det constant
ect rshort ; * rshort was defined in the linreg instruction above
end(system)
estimate(outsigma=v)
```

8. Chapter 6 of the *Programming Manual* uses the variables *Tbill* and *Tblyr* on the file *QUARTERLY.XLS* to illustrate both the Johansen and Engle–Granger cointegration tests.

Notes for EViews Users

- In the Instructors' Manual, the workfile *aets4_ch6_q8.wf1* contains the variables *tbill* and *tblyr*. The *tbill* rate is the same one as used in Question 4. The TABLE *parta_tbill* contains the results of the Dickey–Fuller test for *tbill*. To reproduce the results, open *tbill* and from the **View** tab select **Unit Root Test**. In the dialogue box, choose the **Augmented Dickey–Fuller** and for **Lag length** select **t-statistic** with a **Maximum Lags** of 8. Repeat for *tblyr*.
- Use **Quick** and **Estimate Regression** to estimate the desired regression; enter `tbill c tblyr` to obtain the results reported in the TABLE *partb*. The equation is named *eq_partb*.

- From the Proc tab select `Make Residual Series` and call the residuals *residuals*. Open this residual series and select `Unit Root Test` from the View tab. The TABLE *partc* contains the results using 7 lags.
- The TABLE *partd* contains the estimated error correction model. Open the GROUP *var* to see how the results were obtained. Select `Estimate VAR` from the Quick menu. In `VAR Specification`, select `Vector Error Correction` and use 7 lags and on the `Cointegration` tab use option 2 (constant in the cointegrating vector only).
 - Open *vec* and select `Cointegration Test` from the View tab. Use 7 lags and select button 2 for the choice of deterministic trends. The results are in *parte*.

The question is answered in the Programming Manual using RATS.

9. The file COINT_PPP.XLS contains monthly values of the Japanese, Canadian, and Swiss consumer price levels and the bilateral exchange rates with the United States. The file also contains the U.S. consumer price level. The names on the individual series should be self-evident. For example, *JAPANCPI* is the Japanese price level and *JAPANEX* is the bilateral Japanese/U.S. exchange rate. The starting date for all variables is January 1974 while the availability of the variables is such that most end near the end of 2013. The price indices have been normalized to equal 100 in January 1973 and only the U.S. price index is seasonally adjusted.

Notes for EViews Users

- In the Instructors' Manual, the workfile *aets4_ch6_q9.wf1* contains the variables *japancpi*, *japanex*, *swcpi*, *swex* and *uscpi*. The logarithms are preceded by letter *l* and *dex*, *djp* and *dusp* are the growth rates of *japanex*, *japancpi*, and *uscpi*. The unit root tests are reported in the TABLES *parta_japancpi*, *parta_japanex* and *parta_uscpi*.
- The estimated long-run relationship is in the TABLE *partb*. From the Quick tab select `Estimate Regression` and enter `ljapanex c ljapancpi luscpi`. Now, from the Proc tab select `Make Residual Series` and call the residuals *resid01*. Open *resid01* and select `Unit Root Test` from the View tab. Do not include an intercept or a trend.
- To obtain the results in *parte*, from the Quick tab select `Estimate Regression` and enter `ljapanex c ljapancpi luscpi`.
- To estimate the error-correction model, select `Estimate VAR` from the Quick menu. In `VAR Specification`, select `Vector Error Correction` and use 11 lags. On the `Cointegration` tab use option 2 (constant in the cointegrating vector only). The results are in the TABLE *vec_parte*.
- Select `Impulse` and use the defaults to obtain the impulse responses. To obtain the variance decompositions, from *vec_parte*, select `Variance Decompositions` from the View tab.

Sample Program for RATS Users

Read in the data set using

```
cal(m) 1974:1
all 2013:11
open data c:\aets4\chapter_6\coint_ppp.xlsx
data(org=obs,format=xlsx)
```

- Form the log of each variable and pretest each for a unit root.

```
*One way to form the logs is to use
dofor i = uscpi to swcpi
  set %s("l"+%l(i)) = log(i{0})
end dofor i
```

- To obtain the error-correction model use:

```

@varlagselect(lags=12,crit=gtos,signif=0.05) ; # lJapancpi luscpi lJapanex
system(model=ppp)
var luscpi lJapancpi lJapanex
lags 1 to 12
det constant
ect japan
end(system)
estimate(outsigma=s,residuals=residsjapan)

```

10. In Question 9, you were asked to use the Engle–Granger procedure test for PPP among the variables $\log(\text{canex})$, $\log(\text{cancpi})$, and $\log(\text{uscpi})$. Now use the Johansen methodology and constrain the constant to the cointegrating vector.

Notes for EViews Users

1. In the Instructors' Manual, the workfile *aets4_ch6_q10.wfl* uses the results from Question 9. The *var vec_parte* is reproduced from the workfile *aets4_ch6_q9.wfl*.
2. To perform the Johansen test, open *vec_parte* and from the View tab select Cointegration Test. The results are in the TABLE named *parta*.

Sample Program for RATS Users

To perform the results using the Johansen method use;

```

@johmle(lags=12,determ=rc)
# lcanex lcancpi luscpi

```

CHAPTER 7

NONLINEAR MODELS AND BREAKS

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Questions and Exercises

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Key Concepts

1. Once you abandon the linear framework, it is necessary to select a specific nonlinear alternative. Unfortunately, the literature does not provide a solid framework for this task. It is possible to estimate a series as a GAR, Bilinear, TAR, LSTAR, ESTAR, Markov switching, or ANN process. General tests for nonlinearity do not have a specific alternative hypothesis. Lagrange Multiplier tests generally accept a number of nonlinear alternatives. The issue can be illustrated by the estimate industrial production series beginning on page 419. Although a nonlinear model may be appropriate, the final TAR specification is a bit doubtful. My own view is that an underlying theoretical model should guide the model selection process. For example, in Section 7, a TAR model was used since theory suggests that low-terrorism states should be more persistent than high-terrorism states. To make the point, I rely heavily on Questions 1 and 2. Question 1 is designed to give the student practice in formulating a nonlinear model that is consistent with an underlying economic model. Question 2 asks the student to think about the nature of the nonlinearity that is suggested by any particular nonlinear estimation. In guiding the class discussion, you might want to make an overhead transparency of Figure M7.1 below.

2. The estimation of many nonlinear models requires the use of a software package with a programming language. Although the syntax explained in RATS Programming Manual may not be directly compatible with your software package, the logic will be nearly identical. As such, you can have your students read the following sections of the Programming Manual: Nonlinear Least Squares in Chapter 1.4, Do Loops in Chapter 3.1; If-Then-Else Blocks in Chapter 4.1, and Estimating a Threshold Autoregression (beginning on page 130).

3. For RATS users, the answers to Questions 8, 9 and 10 are in the Programming Manual. As such, they are not reproduced here.

Selected Answers to Questions

4. The file labeled LSTAR.XLS contains the 250 realizations of the series used in Section 9.

Notes for EViews Users

1. In the Instructors' Manual, the workfile *aets4_ch7_q4.wfl* contains 250 observations of the variable y . To generate equation (7.24), open the Quick tab, select Estimate Equation and enter $y = c + y(-1)$. The results are in TABLE *eq_725* and in EQUATION *eq724*. Open *eq724*, and experiment with other linear specifications.
2. To perform the RESET, Open *eq724* and from the View tab select Stability Diagnostics and Ramsey's RESET Test. Even though "RESET test" is redundant, you often see it appear this way in the literature. If you enter 3 for Number of Fitted Terms, you should obtain the same output as in the TABLE *reset*.
3. To perform the BDS test, open the series y and from the View tab select BDS Independence Test. If you use the defaults, you should obtain the results in the TABLE *bds*.
4. Generate the series y_2 , y_3 and y_4 as y^2 , y^3 , and y^4 . From Quick and Estimate Equation enter $y = c + y(-1) + y_2(-1) + y_3(-1) + y_4(-1)$. The results are in *lmtest*.

Dependent Variable: Y
 Method: Least Squares
 Date: 08/10/14 Time: 14:03
 Sample (adjusted): 2 250
 Included observations: 249 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.211127	0.214742	5.639923	0.0000
Y(-1)	1.258764	0.076699	16.41179	0.0000
Y2(-1)	-0.026978	0.027325	-0.987323	0.3245
Y3(-1)	-0.032880	0.002854	-11.52066	0.0000
Y4(-1)	-0.003187	0.000658	-4.843551	0.0000

You can perform the LM test by selecting Coefficient Diagnostics from the View tab. Then select Wald Test and enter $c(3) = c(4) = c(5) = 0$.

5. To estimate the GAR model, from the Quick tab, estimate the regression:
 $y = c + y(-1) + y(-2) + y_2(-1)$. The results are reported in the TABLE *gar*.

Sample Program for RATS Users

```
all 250 ;* The first three lines read in the data set
open data c:\aets3\lstar.xls
data(format=xls,org=obs)
```

d. Perform the LM test for LSTAR versus ESTAR adjustment. Let y_{t-1} be the delay parameter

```
set delay = y{1}
* To determine if  $y_{t-2}$  should be the delay parameter, use: set delay = y{2}
* Now, multiply  $y_{t-1}$  by the powers of delay parameter.
set y1d = y{1} * delay
set y1d2 = y{1} * delay**2
set y1d3 = y{1} * delay**3
```

5. The file GRANGER.XLS contains the interest rate series used to estimate the TAR and M-TAR models in Section 11.

Notes for Eviews Users

1. In the Instructors' Manual, the workfile *endersgranger.wfl* contains the results reported in Section 11. The file contains the variable *s* generated as: $s = r_{10} - s_{\text{short}}$. The variables *ds*, *drl* and *drs* were generated using: $ds = d(s)$, $drl = d(r_{10})$ and $drs = d(r_{\text{short}})$. The unit root test for *s* is reported in the TABLE *df_spread*. From the View tab select Unit Root Test, include only an intercept (no trend) and User Specified lag of 1.
2. In order to estimate the TAR model, it is first necessary to generate the threshold variables *s_plus* and *s_minus*. Given that the threshold is 0.27, you can use the @recode function as follows:

```
s_plus = @recode(s(-1)+0.27>0,s(-1)+0.27,0)
s_minus = @recode(s(-1)+0.27<=0,s(-1)+0.27,0)
```

To obtain the results in the TABLE *p464_tar*, select Estimate Equation from the View tab and enter: `s s_plus s_minus s(-1)`. Do not include separate intercept terms as these are already embedded in the continuous form of the TAR model.

3. In order to estimate the M-TAR model, it is necessary to create the threshold variables *mtar_plus* and *mtar_minus*. Given that the threshold is zero for the M-TAR model, this is accomplished using


```
mtar_plus = @recode(ds(-1)>0,s(-1)-1.64,0)
mtar_minus = @recode(ds(-1)<=0,s(-1)-1.64,0)
```

To obtain the results in the TABLE *p264_mtar*, select Estimate Equation from the View tab and enter: `ds mtar_plus mtar_minus ds(-1)`.

4. Equation 465 contains the estimates of the M-TAR error-correction model. Select Estimate Equation from the View tab and enter:

```
drl mtar_plus mtar_minus drs(-1 to -2) drl(-1 to -2)
drs mtar_plus mtar_minus drs(-1 to -2) drl(-1 to -2)
```

The results are in the TABLES *drl_mtar* and *drs_mtar*. You can open the EQUATION *drlmtar* to experiment with the estimates.

RATS programmers can estimate the TAR and M-TAR models using

```
cal 1958 1 4          ;* These four lines read in the data set. The data begin in
all 8 1994:1         ;* 1958Q1 and end in 1994Q1
open data c:\aets3\granger.xls
data(format=xls,org=obs)
```

```
set spread = r_10 - r_short          ;* Create spread as the difference between the 10-year rate
dif spread / ds                      ;* and the short rate. Take the first difference of spread
```

```
* Perform the Dickey-Fuller test on the spread. Save the residuals as resids
lin ds / resids; # constant spread{1} ds{1}
```

7. The file labeled SIM_TAR.XLS contains the 200 observations used to construct Figure 7.3. You can answer the questions in the test using the following:

Notes for Eviews Users

1. The workfile *aets4_ch7_q7.wfl* contains the variables *y* and *ordered*. *Ordered* are the ordered values of the *y* series arranged from low to high. You can reproduce Figure 7.4 by plotting the *ordered* series. The TABLE *parta* contains the desired regression equation. Select `Estimate Equation` from the View tab and enter:

```
y c y(-1).
```

To perform the RESET, Open *eq01* and from the View tab select `Stability Diagnostics` and `Ramsey's RESET Test`. If you enter 3 for `Number of Fitted Terms`, you should obtain the same output as in the TABLE *reset*. The point to note is that the RESET does not indicate any nonlinearity.

2. EViews cannot readily perform a repetitive set of estimations within a DO loop. It is possible to estimate a TAR models using various threshold values and select the best fitting value. Hence, if you know $\tau = 0$ you could use the following two instructions to generate the indicator functions

```
plus = @recode(y(-1)>0,1,0)
minus = @recode(y(-1)<=0,1,0)
```

Next, use `Quick Estimate Equation` and enter:

```
y plus minus plus*y(-1) minus*y(-1)
```

The results are in the TABLE *tar* and in EQUATION *eq02* Note that this is different from the result reported in the text since the estimation uses $\tau = -0.4012$.

3. If you want to use $\tau = -0.4012$ generate *plus* and *minus* using:

```
plus = @recode(y(-1)>-0.4012,1,0)
minus = @recode(y(-1)<=-0.4012,1,0)
```

Sample Program for RATS Users

```
* Read in the data
all 200
open data c:\aets3\sim_tar.xls
data(format=xls,org=obs)
```

- a. You can estimate the series as $y_t = -0.162 + 0.529y_{t-1} + e_t$ using


```
set y = tar
lin y / resids; # constant y{1}
```

- c. To plot the residuals sum of squares for each potential threshold value you can use


```
* THRESHTEST.SRC. The procedure will also perform Hansen's test for a threshold process.
```

```
source c:\aets3\threshtest.src
set thresh = y{1} ; * use a delay value of 1
@threshtest(thresh=thresh,graph,nreps=1000,trim=.1) y ; # constant y{1}
```

8. Chapter 3 of the *Programming Manual* contains a discussion of the appropriate way to program smooth transition regressions, ESTAR models, and LSTAR models. If you have not already done so, download the manual from the Estima (Estima.com) or the Wiley Web site.

Notes for EViews Users

1. In the Instructors' Manual, the workfile *aets4_ch7_q8.wfl* contains the variables *ppi* and $pi = 400 * \log(ppi/ppi(-1))$. The TABLE *parta* contains the *pi* series estimated as an AR(4). *s* indicated in the *Programming Manual*, **be sure that the estimation starts in 1983Q1 not at the beginning of the data set.**
2. As was the case shown in the *Programming Manual* the LSTAR model does not perform especially well. As reported in the TABLE *lstar*, it is very difficult to achieve convergence. Notice that the estimation stopped after only one iteration—the results are meaningless. The EQUATION *eq_lstar* allows you to experiment with the

model.

11. The file OIL.XLS contains the variable SPOT measuring the weekly values of the spot price of oil over the May 15, 1987 – Nov 1, 2013 period. In Section 4 of Chapter 3, we formed the variable $p_t = 100[\log(\text{spot}_t) - \log(\text{spot}_{t-1})]$ and found that it is reasonable to model p_t as an MA($\|1,3\|$) process. However, another reasonable model is the autoregressive representation: $p_t = 0.095 + 0.172p_{t-1} + 0.084p_{t-3}$. The issue is to determine whether the $\{p_t\}$ series contains breaks or nonlinearities.

Notes for Eviews Users

1. The file *aets4_ch_7_q11.wfl* contains the price of oil (*spot*) and the series $p = 100*d\log(\text{spot})$. TABLE *parta* and EQUATION *eq_parta* contain the results from estimating the p series as an AR($\|1,3\|$) process. To obtain the result in the TABLE *cusum* select View Stability Diagnostics and Recursive Estimates. From the Output box, select CUSUM test.
2. To test for a single breakpoint, select View Stability Diagnostics and choose Quandt-Andrews Breakpoint Test. If you use the default 15% trimming, you should obtain the results reported in Table *partb*.
3. To perform the Bai-Perron test select View Stability Diagnostics and choose Multiple Breakpoints Tests. Select Global L breaks vs. none, use a maximum of 5 breaks and the default trimming and significance level. The results in TABLE *partc* indicate that there are no breaks.
4. To estimate the model given that $\tau = 1.7$, use GENERATE to form the following variables

```
plus = @recode(p(-1)>1.7,1,0)
minus = @recode(p(-1)<=1.7,1,0)
p1_plus = p(-1)*plus
p3_plus = p(-3)*plus
p1_minus = p(-1)*minus
p3_minus = p(-3)*minus
```

From Quick Estimate Equation enter
p plus p1_plus p3_plus minus p1_minus p3_minus
The results are in *eq_partd*.

5. From Quick Estimate Equation enter
p p1_minus p3_minus

Sample Program for RATS Users

```
end(reset)
CAL(w) 1987 5 15
all 2013:11:1
open data c:\aets4\chapter_3\oil.xls
data(org=obs,format=xls)
tab

set rate = 100.0*(log(spot)-log(spot{1}))
set y = rate
lin y ; # constant y{1 3}
```

SEMESTER PROJECT

The best way to learn econometrics is to estimate a model using actual data. At the beginning of the semester (quarter), students should identify a simple economic model that implies a long-run equilibrium relationship between a set of economic variables. Data collection should begin as early as possible so that the econometric tests can be performed as they are covered in class. Some students may be working on projects for which they have data. Others should be able to construct a satisfactory data set using the internet. Some of the web sites that were used in writing the test are

1. www.fedstats.gov/ The gateway to statistics from over 100 U.S. Federal agencies such as the Bureau of Labor Statistics, the Bureau of Economic Analysis, and the Bureau of the Census.
2. www.research.stlouisfed.org/fred2/ The St. Louis Fed Database. With over 1000 downloadable economic variables, this is probably the best site for economic time-series data.
3. www.nyse.com/marketinfo/marketinfo The New York Stock Exchange: The Data Library contains daily volumes and closing prices for the major indices
4. www.oecd.org/statistics/ The statistics portal for the Organization for Economic Cooperation and Development. Economic indicators, leading indicators, and labor force statistics.

For those who spend too much time searching for a project, students can update MONEY_DEM.XLS. This data set is used in the Programming Manual. The file contains quarterly values of seasonally adjusted U.S. nominal GDP, real GDP in 1996 dollars (RGDP), the money supply as measured by M2 and M3, and the 3-month and 1-year treasury bill rates for the period 1959:1 – 2001:1. Both interest rates are expressed as annual rates and the other variables are in billions of dollars. The data were obtained from the website of the Federal Reserve Bank of St. Louis and saved in Excel format.

The semester project is designed to employ all of the material covered in the text. Each student is required to submit a paper demonstrating competence in using the procedures. I require my students to use the format below. The various sections are collected throughout the semester so that student progress can be monitored. At the end of the semester, the individual sections are compiled into the final course paper. Of course, you might want to adapt the outline to your specific emphasis and to the statistical software package available to you. In Example 1, the student wants to estimate a demand for money function. In Example 2, the student wants to estimate the term structure of interest rates.

1. Introduction

Of course, it is important that students learn to generate their own research ideas. However,

in the short space of a semester (or quarter), it is necessary for students to quickly select a semester project. After two weeks, I ask my students for a page or two containing:

1. A statement of the objective of the paper
2. A brief description of the relevant literature including the equation(s) to be estimated
3. The definition and source of each series to be used in the project. Some mention should be made concerning the relationship between the variables in the theoretical model and the actual data available.

Example 1: The student discusses why the demand for money can be represented by:

$$m_t = \beta_0 + \beta_1 y_t + \beta_2 r_t + p_t + e_t$$

where: m_t = money supply (=money demand), y_t = measure of income or output; r_t = vector of interest rates; p_t = price index; t is a time-subscript; e_t is an error-term; and all variables are measured in logarithms. Note that these variables are included on the data set MONEY_DEM.XLS.

Example 2: The student discusses why the term structure of interest rates implies a relationship among short-term and long-term interest rates of the form:

$$TBILL_t = \beta_0 + \beta_1 R3_t + \beta_2 R10_t + e_t$$

where: $TBILL_t$ is the treasury bill rate, $R3_t$ is a three-year rate and $R10_t$ is a ten year rate. Note that these three variables are on the file INT_RATES.XLS.

2. Difference equation models

This portion of the project is designed to familiarize students with the application of difference equations to economic time-series data. Moreover, the initial data manipulation and creation of simple time-series plots introduces the student to the software at an early stage in the project. In this second portion of the paper, students should:

1. Plot the time path of each variable and describe its general characteristics. There should be some mention of the tendencies for the variables to move together.
2. For each series, develop a simple difference equation model that mimics its essential features.

Example 1: This portion of the paper contains time-series plots of the money supply, output, interest rate(s), and price index. The marked tendency for money, output and prices to steadily increase is noted. Periods of tranquility and volatility are indicated and the student mentions that the periods are similar for all of the variables. The student indicates that a

difference equation with one or more characteristic root lying outside the unit circle might capture the time path of the money supply, price index, and level of output.

Example 2: This portion of the paper contains time-series plots of the various interest rate series. The tendency for the rates to meander is noted. The student shows how difference equations with a characteristic root that is unity can mimic the essential features of the interest rate series. It is also shown that characteristic roots near unity will impart similar time-paths to the series. The tendency for the rates to move together and any periods of tranquility and volatility are mentioned.

3. Univariate properties of the variables

This portion of the project introduces the student to the tools used in estimating the univariate properties of stationary time-series. Chapter 2 provides the necessary background material. The student should select two or three of the key variables and for each:

1. Estimate an ARIMA model using the Box-Jenkins technique.
2. Provide out-of-sample forecasts. There should be some mention of the forecasting performance of the models.

Example 1: The Box-Jenkins method suggests several plausible models for the money supply. Each is examined and compared in detail since the project focuses on money demand.

Example 2: The three interest rate series are estimated using the Box-Jenkins methodology. The focus is not on any single interest rate series. Instead, several reasonable models for each series are found. Tests for the presence of GARCH and ARCH-M effects are presented.

4. Conditional Volatility

I allow students some flexibility in proceeding at this point. Some students will have a keen interest in financial econometrics. These students should select two financial variables and test each for the presence of GARCH effects. They should be able to present a well-reasoned GARCH model for each series. I put particular importance on the justification of the most appropriate specification. I also ask them to estimate the two series as a multivariate GARCH process. They should be able to compare several different multivariate specifications. Students selecting this option need not spend much time on Section 5 below. For most financial variables, simple differencing or constructing the growth rate will result in a process that is stationary and not very persistent.

Students who select non-financial variables should be each for the presence of GARCH and/or ARCH-M effects. I expect these students to place more emphasis on the topic in Section 5 below.

5. Estimates of the trend

Most students will select one or more variables that exhibit evidence of non-stationary behavior. In this portion of the project, students should:

1. Use the material in the Chapter 4 to discuss plausible models for the trends. The goal is to refine the difference equation model suggested in Step 2 of the project.
2. Decompose the variables into their temporary and permanent components.
3. Use the material in Chapter 4 to conduct formal tests for unit roots and/or deterministic time trends. There can be a comparison of the effects of "detrending" versus differencing a series showing evidence of a trend.
4. Potentially important seasonal effects and/or evidence of structural change should be noted. If warranted, seasonal unit root tests and/or Perron tests for unit roots in the presence of structural breaks should be conducted.

Example 1: The money supply is decomposed into its temporary and permanent components using a Beveridge-Nelson decomposition. Dickey-Fuller tests for unit roots in the money supply series are conducted. The various tests for the presence of drift and/or time trends are also conducted. Given that the Federal Reserve has changed its operating procedures, the money supply is tested for unit roots in the presence of a structural break.

Example 2: The long-term rate is decomposed into its temporary and permanent components using a Beveridge-Nelson decomposition. Dickey-Fuller tests for unit roots in all of the interest rate series are conducted. The presence of unit roots in the interest rate series is mixed. It may be that the interest rates are near unit root processes. The student compares the ARMA estimates of the long-term rate using levels, "detrended" values, and first-differences of the data.

6. Vector Autoregression Methods

This portion of the project introduces multiple time-series methods. Chapter 5 of the text provides the background material necessary for the student to estimate a VAR. The student should complete the following tasks:

1. Estimate the variables as a VAR. The relationship among the variables should be analyzed using innovation accounting (impulse response functions and variance decomposition) methods.
2. Compare the VAR forecasts to the univariate forecasts obtained in Step 3 of the project.
3. A structural VAR using the Sims-Bernanke or Blanchard and Quah techniques should be attempted.

Example 1: The money supply, income level, interest rate and price level are estimated as

an autoregressive system. It is reported that the univariate forecasts from Step 3 are nearly the same as those from the VAR. Granger causality tests are performed in order to pare down the model. A Choleski decomposition with various orderings is used to decompose the forecast error variances of the variables. Impulse response functions are used to examine the effects of the various shocks on the demand for money. The student estimates a structural VAR such that contemporaneous real income and interest rate shocks are unaffected by the other variables in the system.

Example 2: The student estimates the three interest rates as a VAR. Since the issue of stationarity is unclear, the student estimates the VAR in levels and in first-differences. A Choleski decomposition with various orderings is used to decompose the forecast error variances of the variables. Impulse response functions are used to show the effects of shocks to 10-year and 3-year rates on short-term rates. The student uses a bivariate VAR to decompose the 10-year interest rate into its temporary and permanent components.

7. Cointegration

This portion of the project introduces the concept of cointegration. Chapter 6 of the text provides the appropriate background. The student should:

1. Conduct Engle-Granger and Johansen tests for cointegration
2. Estimate the error-correction model. The error-correction model should be used to analyze the variables using innovation accounting techniques.

Example 1: For some specifications, the Engle-Granger and Johansen tests for cointegration will reveal a long-run equilibrium relationship among the variables. For other specifications and other sample periods, there is no credible money demand function. If the variables are not cointegrated, the error-correction model is not estimated since the variables are not cointegrated. Instead, the student discusses some of the credible reasons underlying the rejection of the theory as presented.

Example 2: The Engle-Granger and Johansen tests for cointegration reveal a long-run equilibrium relationship among the interest rates. The error-correction model is estimated. Innovation accounting is conducted; the results are compared to those reported in Step 5.

8. Nonlinearity

The last portion of the project uses nonlinear time-series models presented in Chapter 7. The student should:

1. Discuss a possible reason why a nonlinear specification might be plausible.
2. Conduct a number of tests that are capable of detecting nonlinearity.
3. Compare the linear estimates to the estimates from a nonlinear model.

Example 1: One reason why Engle-Granger and Johansen tests may fail is that they implicitly assume a linear adjustment mechanism. The student tests the variables for linear versus nonlinear behavior.

Example 2: The text suggests that interest rate spreads are nonlinear. An inverted yield curve is far less persistent than a situation when short-term rates are below long-term rates. A nonlinear model of the spread is estimated and compared to the linear model.