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1 Loading data to EViews

In this review session, we will be working with data on U.S. Treasuries (T-bills). The data is saved as Tbills.xls on the webpage. Before analyzing the data, we will briefly go over how to set-up an EViews session and to load data into an EViews workfile. Remember that a lot of things in EViews can be done either through the drop-down menus at the top of the EViews window or through commands in the command line (which you can then save for future use in a program). Where applicable, I will try to provide both the menu paths and the command line prompts.

1.1 Using menus to create an empty workfile:

Step 1. Open Eviews. Notice that there is no blank document for you to start your work in. Instead, what you see is the command pane at the top of the window.

Step 2. To create a new workfile, use the menu to choose File/New/Workfile...

Step 3. Once you have the Workfile Create dialog box displayed, choose Dated-regular frequency from the Workfile structure type dialog box and Monthly from the Frequency dialog box, since the T-bill data we will be using has regular (i.e. no observations skipped), monthly observations. Also, input the start date (1982m1) and end date (2009m11) into the Start date and End date dialog boxes.

Step 4. If you like, you can specify a name for the workfile in the WF box.

1.2 Using command panel to create an empty workfile:

Step 1. Open Eviews. Notice that there is no blank document for you to start your work in. Instead, what you see is the command pane at the top of the window.

Step 2. To create a new workfile with monthly observations, type: wfcreate m 1982m1 2009m11

1.3 Using the Excel file to create a workfile:

Step 1. Open Eviews.

Step 2. To load an Excel file as a new workfile, use the menu to choose File/Open/Foreign Data as Workfile and point to the Tbills.xls file.

Step 3. EViews analyzes the excel file and opens a Spreadsheet read dialog box. Most of the time, you should be able to just click on the Finish button and the data
will be properly imported. EViews will also generally recognize that the date column in the Excel file should be used to identify the different data points.

2 Time Series Data and the Autocorrelation Function

Time-series data are a collection of observations gathered over time. To plot the T-bill data we imported, select the imported series and choose View/Graph from the pull-down menu. This brings up the Graph Options dialog box. To create the simple line graph below, click the OK button.

Figure 1: Time-series evolution of monthly T-bill rates

![Yields on T-bills graph](image)

**Question 1.** *Does this look i.i.d?*

Recall that it’s not always easy to just look at a time-series plot and say whether or not the series is independent. Saying that the \( Y_t \) series is independent means that knowing previous values does not help you to predict the next value. To summarize all
of the plots of $Y$ versus lagged $Y$s, we compute the correlations between $Y_t$ and $Y_{t-L}$ for $L = 1, 2, 3, \ldots$. These correlations between $Y$ and lagged values of $Y$ are called autocorrelations. The autocorrelation function (or acf), given any lag value $L$, simply returns the autocorrelation for lag $L$. Let’s revisit our dataset which contains monthly yields for treasury bills and construct the respective autocorrelation function for the 3-month T-bill rate, the first series in our file. To create the graph below, open the series corresponding to the yield on the 3-month T-bill and, from the drop down menu, select View/Correlogram. This displays the Correlogram Specification dialog box. Select level in the Correlogram of: drop-down menu and enter 20 in the Lag Specification: lags to include box.

![Figure 2: 3-month T-bill yield correlogram](image)

**Side Note:** EViews considers a correlogram to be a table. When you save the correlogram, EViews converts the bars in the plots of the autocorrelation and partial autocorrelation into stars. To create a graph with the autocorrelation function (or partial autocorrelation function), select the appropriate (numeric) columns inside the correlogram, copy and then right click in the blank space in the EViews window to paste. This will create a new workfile with the autocorrelation values stored as series. You can then proceed to graph them as usual.

**Question 2.** What does the ACF plot suggest?

**Question 3.** How many lags am I including in the ACF plot?
Notice that we entered 20 in the **Lag Specification: lags to include** box. This argument specifies the maximum number of lags to display in the plot. Notice also that the correlogram also displays the **partial autocorrelation function** (pacf), as well as the actual values of the acf and the pacf. The values correspond to the autocorrelation at that specific lag. For example, at lag 1, we have an autocorrelation of 0.976.

**Question 4.** How do we deem an autocorrelation at a given lag to be significant?

In our example, we can see from the top of our workfile that we have 335 observations. Thus, the cut-off point for the acf is:

\[ \frac{2}{\sqrt{T}} = \frac{2}{335} \approx 0.11 \]

**Question 5.** Up to which lag do we have a significant autocorrelation?

**Question 6.** If none of the autocorrelations are significantly different from zero, what does this suggest?

### 3 Estimating an AR(1) model

After we have constructed an ACF plot, we take a stand on whether we have dependence in our time series dataset. Once we’ve decided that observations are not independent over time, we model this dependence with a time series model. In this section, we consider a simple time-series model known as the AR(1) model. AR stands for autoregressive. Formally the model is given by:

\[ Y_t = \beta_0 + \beta_1 Y_{t-1} + \epsilon_t; \quad \epsilon \sim i.i.d. N(0, \sigma^2). \]

**Question 7.** What does this model say about the evolution of \( Y \) over time?

**Question 8.** Which part of \( Y \) depends on the past?

**Question 9.** Which part of \( Y \) is not predictable from the past?

The EViews computing environment provides a wide array of commands for the modeling of time series data. In this session, we aim to provide techniques in simulating, estimating, and forecasting the class of AR models. We begin by estimating an AR(1) specification for the 3-month T-bill data we imported above. The easiest way to estimate an AR(1) model in EViews is to type:

```plaintext
ls yield3m c ar(1)
```

in the command window. The components in the above formula are:
• ls: tells EViews that we want to estimate a least-squares (ls) regression

• yield3m: the dependent variable in the regression. For our example, I’m using the yield on 3-month T-bills, which I’ve named yield3m in my workfile

• c: tells EViews to estimate a constant in the regression

• After the constant, we list the independent variables. In this case, since we are interested in estimating an AR(1) model, we only include the AR(1) term, ar(1).

The results of the regression are shown in the Table below. **Side Note:** As with the Correlogram, the estimated coefficients and the regression statistics are treated as tables in the EViews environment. If you are using Word to create your text documents, you can save the table as a .csv file and then just import it into Word.

Table 1: Estimated coefficients and regression statistics for the AR(1) model of the 3-month T-bill yield.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>2.327633</td>
<td>1.782911</td>
<td>1.305524</td>
<td>0.1926</td>
</tr>
<tr>
<td>AR(1)</td>
<td>0.986213</td>
<td>0.006288</td>
<td>156.8343</td>
<td>0.0000</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.986682</td>
<td>Mean dep. var</td>
<td>5.083952</td>
<td></td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.986642</td>
<td>S.D. dep. var</td>
<td>2.717580</td>
<td></td>
</tr>
<tr>
<td>S.E. of regression</td>
<td>0.314089</td>
<td>Akaike info crit.</td>
<td>0.527687</td>
<td></td>
</tr>
<tr>
<td>Sum squared resid.</td>
<td>32.75235</td>
<td>Schwarz criterion</td>
<td>0.550508</td>
<td></td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-86.12369</td>
<td>Hannan-Quinn crit.</td>
<td>0.536786</td>
<td></td>
</tr>
<tr>
<td>F-statistic</td>
<td>24596.99</td>
<td>Durbin-Watson stat</td>
<td>1.174007</td>
<td></td>
</tr>
<tr>
<td>Prob(F-statistic)</td>
<td>0.000000</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Inverted AR Roots .99

**Question 10.** What is the standard error corresponding to the intercept?

**Question 11.** What is the standard error corresponding to the autoregressive coefficient?

**Question 12.** What is the intercept measuring here?

**Question 13.** How do we write out the final model?

Notice that EViews automatically extracts the residuals for you into the series resid. Unfortunately, this series is updated every time you run a regression. The solution is to save the residuals you want as separate series. For example, we can save the regression coefficients for the 3-month T-bill rate by typing:
series res3m=resid

in the command window. This tells EViews to create a new series called res3m and to assign to it the values stored in the series resid. The plot of the residuals is below (Fig. 3).

Figure 3: AR(1) residuals

Question 14. Having estimated an AR(1) model, why do we check the residuals for dependence?

We can construct a correlogram of the residuals following the same steps as above.

Question 15. What does the ACF plot of the residuals suggest?

Question 16. Is an AR(1) model a good model?

Question 17. For an AR(1) model, what happens if $|\beta_1| = 1$?

Question 18. For an AR(1) model, what happens if $|\beta_1| > 1$?

4 Simulating an AR(1) model

For these exercises, open a new page in the EViews workfile and choose Unstructured/Undated from the Workfile structure type pull-down menu. In the Observations: box, enter 1000.
4.1 Example 1

Suppose we want to simulate 1000 observations from an AR(1) model with lag parameter 0.9. Specifically, we aim to simulate from the following AR (1) model:

\[ y_t = 0.9y_{t-1} + \epsilon_t; \quad \epsilon_t \sim \text{i.i.d. } N(0,1). \]

To simulate this in EViews, enter the following commands in the command window:

```
smpl @all
series example1=0
smpl @first+1 @last
example1=0.9*example1(-1)+nrnd
```

The explanation for these commands is as follows:

- **smpl @all**: this tells EViews that you will be working with the full sample in the page (until otherwise specified)

- **series example1=0**: this creates a new series object in EViews with the name “example1” and assigns 0 to each entry.

- **smpl @first+1 @last**: define the sample to start at the second observation
• example1=0.9*example1(-1)+nrnd:
  - example1(-1): takes the observations in example1, lagged by one observation
  - nrnd: creates draws from a standard normal

The simulated series is presented in Fig. 5.

Figure 5: Simulated path of $y_t = 0.9y_{t-1} + \epsilon_t$

---

**Question 19.** What is the unconditional mean?

### 4.2 Example 2

Suppose now we want to simulate 1000 observations from an AR(1) model with lag parameter -0.9. Specifically, we aim to simulate from the following AR (1) model:

$$y_t = -0.9y_{t-1} + \epsilon_t; \quad \epsilon_t \sim_{i.i.d.} N(0, 1).$$

To simulate this in EViews, enter the following commands in the command window:

```eviews
smpl @all
series example2=0
smpl @first+1 @last
example2=-0.9*example2(-1)+nrnd
```
Figure 6: Simulated path of $y_t = -0.9y_{t-1} + \epsilon_t$

The simulated series is presented in Fig. 6.

**Question 20.** How does this compare with the previous simulated model?

**Question 21.** How can we see the difference besides the time series plots?

### 4.3 Example 3

Suppose now we want to simulate 1000 observations from an AR(1) model with lag parameter 0.75 and intercept 0.5. Specifically, we aim to simulate from the following AR(1) model:

$$y_t = 0.5 + 0.75y_{t-1} + \epsilon_t; \quad \epsilon_t \sim_{i.i.d.} N(0,1).$$

To simulate this in EViews, enter the following commands in the command window:

```
smpl @all
series example3=0
smpl @first+1 @last
example3=0.5+0.75*example3(-1)+nrnd
```

The simulated series is presented in Fig. 7.

**Question 22.** What is the unconditional mean?

**Question 23.** How can we check the variance of the innovation terms?
5 Estimating an AR(p) model

Recall that if the AR(1) model doesn’t capture the dependence in the data, you can try a multiple regression with higher lags of Y thrown in:

\[
Y_t = \beta_0 + \beta_1 Y_{t-1} + \ldots + \beta_p Y_{t-p} + \epsilon_t; \quad \epsilon_t \sim i.i.d. N(0, \sigma^2).
\]

This model is called an autoregressive model of order \( p \).

**Question 24.** What does this model say about the evolution of \( Y \) over time?

**Question 25.** Which part of \( Y \) depends on the past?

**Question 26.** Which part of \( Y \) is not predictable from the past?

Let’s revisit our 3-month T-bill yield series and estimate a higher order AR model. In particular, we will estimate an AR(6) model using the command:

\[\text{ls yield3m c ar(1) ar(2) ar(3) ar(4) ar(5) ar(6)}\]

The table below presents the estimation results.

**Question 27.** What are the standard errors for our estimates?
Table 2: Estimated coefficients and regression statistics for the AR(6) model of the 3-month T-bill yield.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>3.876576</td>
<td>0.957422</td>
<td>4.048973</td>
<td>0.0001</td>
</tr>
<tr>
<td>AR(1)</td>
<td>1.523288</td>
<td>0.054748</td>
<td>27.82388</td>
<td>0.0000</td>
</tr>
<tr>
<td>AR(2)</td>
<td>-0.726549</td>
<td>0.098243</td>
<td>-7.395444</td>
<td>0.0000</td>
</tr>
<tr>
<td>AR(3)</td>
<td>0.319759</td>
<td>0.102648</td>
<td>3.115090</td>
<td>0.0020</td>
</tr>
<tr>
<td>AR(4)</td>
<td>-0.121134</td>
<td>0.098504</td>
<td>-1.229737</td>
<td>0.2197</td>
</tr>
<tr>
<td>AR(5)</td>
<td>0.036748</td>
<td>0.087550</td>
<td>0.419740</td>
<td>0.6750</td>
</tr>
<tr>
<td>AR(6)</td>
<td>-0.048737</td>
<td>0.049330</td>
<td>-0.987977</td>
<td>0.3239</td>
</tr>
</tbody>
</table>

R-squared   0.989810          Mean dependent var 4.958419
Adjusted R-squared 0.989620          S.D. dependent var 2.537289
S.E. of regression 0.258508          Akaike info criterion 0.153270
Sum squared resid 21.51817         Schwarz criterion 0.234037
Log likelihood -18.21294         Hannan-Quinn criter. 0.185490
F-statistic 5212.725           Durbin-Watson stat 1.762275
Prob(F-statistic) 0.000000       

Inverted AR Roots
- .28 + .36i
- .28 - .36i
-.18 -.54i .18 + .54i

Question 28. What is our estimate of \( \sigma \)?

Question 29. How do we write out the final model?

Consider now the residuals (see Fig. 8 below). As before, EViews saved the regression residuals into the resid series. Resave these using

```
series resar6=resid
```

and follow the steps above to construct an acf plot.

Question 30. Having estimated an AR(6) model, why do we check the residuals for dependence?

Question 31. What does the ACF plot (Fig. 4 of the residuals suggest?

Question 32. Is an AR(6) model a good model?

Question 33. Does the AR(6) model compete with the AR(1) model?
6 Simulating AR(p) models

Similar to the AR(1) models, it is also easy to simulate AR(p) models using the lag operators and draws from the standard normal.

6.1 Example 4:

Let’s simulate 1000 observations from an AR(2) model with lag parameters 0.75 and 0.1 with intercept 0.5. Specifically, we aim to simulate from the following AR(2) model:

\[ y_t = 0.5 + 0.75y_{t-1} + 0.1y_{t-2} + \epsilon_t; \quad \epsilon_t \sim i.i.d. \, N(0, 1). \]

To simulate this in EViews, type:

```eviews
smpl @all
series example4=0
smpl @first+2 @last
example4=0.5+0.75*example4(-1)+0.1*example4(-2)+nrnd
```

Notice that, since we are simulating an AR(2) model, we start the sample at the third observation when simulating. The simulated series is presented in Fig. 10.

Question 34. What is the unconditional mean?
Question 35. How can we check the variance of the innovation terms?
7 Partial Autocorrelation Function

The partial autocorrelation function (PACF) is one more useful tool for model selection, in the sense of figuring out how many lags to include in the model. The $j^{th}$ partial autocorrelation is the $j^{th}$ regression coefficient in a regression of $y_t$ on $y_{t-1}, y_{t-2}, \ldots, y_{t-j}$.

At the same time that EViews constructs the ACF for a variable, it also constructs the PACF. The PACF for the yield on the 3-month T-bill is below (Fig. 11).

**Question 36.** What does the PACF plot suggest?

**Question 37.** Suppose that the true time series process for the yield on the 3-month T-bill was an AR(1) process, what should the PACF look like? Why?

**Question 38.** When would we reject the null that the $j^{th}$ PAC is zero?

**Question 39.** What behavior does the ACF for an AR($p$) model exhibit?

**Question 40.** What behavior does the PACF for an AR($p$) model exhibit?
Figure 10: Simulated path of $y_t = 0.5 + 0.75y_{t-1} + 0.1y_{t-2} + \epsilon_t$

Figure 11: Partial Autocorrelation Function for the 3-month T-bill yield