EViews: Introductory User Guide

Basic Forecasting

Learning support material for the courses:

- ✓ NMST537 Time Series Analysis
- ✓ NEKN432 Econometrics

Based on official EViews Tutorials & EViews Illustrated.

Forecasting

- EViews offers a powerful and easy-to-use forecasting tool that allows you to obtain forecasts from your estimated models.
- Of course, the accuracy of the forecasts depends on the model used to produce the forecasts: EViews simply handles the mechanics of producing the forecasts. This paper explains the basic procedures for forecasting from a single equation. It assumes knowledge of estimating equations in EViews.
- The main topics of this tutorial are:
  - ✓ Forecast Basics (Static vs. Dynamic, Forecast Evaluation, Errors and Variances)
    - With exogenous variables
    - With lagged dependent variables
    - With lagged dependent variables and ARMA terms
  - ✓ Forecasting with Auto-series

EViews: Introductory User Guide

BASIC FORECASTING: DATA

Data and Workfile Documentation

- ***Partt11.wf1*** contains monthly data from January 1960-March 2013:
  - ✓ ***payroll*** – employment levels, thousands of employees (source: *Bureau of Labor Statistics*)
  - ✓ ***IP*** –industrial production, index levels (source: *Board of Governors of the Federal Reserve*)
  - ✓ ***ISM*** – The Institute for Supply Management Manufacturing Index, Index level (source: *St. Louis' FRED Database*).
  - ✓ ***Tbill 3M***– 3-month US Treasury rate (source: *Board of Governors of the Federal Reserve*)

- ❑ Note that historical data are available for all data series up until March 2013.
- ❑ From *April 2013* until the end of the workfile range, we have provided forecasts for series ***IP***, ***ISM***, ***TBill3m***.
- ❑ We will create a few equations to forecast the ***payroll*** series using EViews.

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BASIC FORECASTING: FORECASTING USING EXOGENOUS VARIABLES

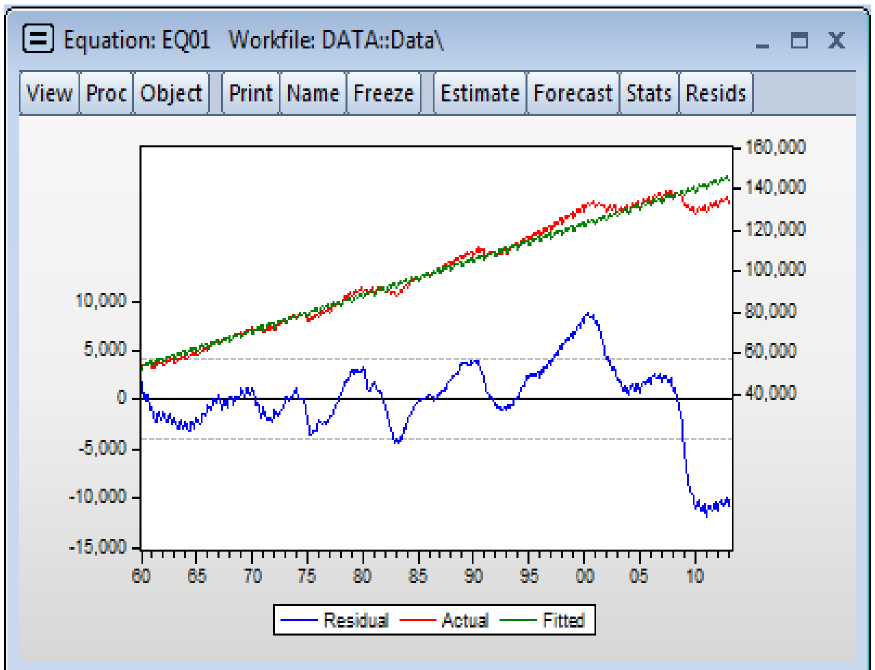
Forecasting with Exogenous Variables: Example 1 (Part I)

- Suppose we want to forecast the level of non-farm payroll employment for the period from *2014m04 to 2014m12*.
- To accomplish this task, we first need to specify and estimate a model. Let us model the payroll level as a linear function of a time trend and seasonal factors:

$$PAYROLL_t = \beta_0 + \beta_1 t + \sum_{j=2}^{12} \beta_j 1_{[t \sim j-th\ month]} + \varepsilon_t, t = 1, \dots, T, \varepsilon_t \sim WN(0, \sigma^2).$$

Forecasting with Exogenous Variables: Example 1 (Part II)

- Estimation output is shown here. Note that EViews has estimated the model over the period *1960m01 to 2013m03*, for which we have ***payroll*** data.
- We also plot the actual and fitted values of the model (shown below), by pressing ***View → Actual, Fitted, Residual → Actual Fitted Residual Graph***.



Equation: EQ01 Workfile: DATA::Data\

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: PAYROLL
Method: Least Squares
Date: 05/11/13 Time: 19:25
Sample (adjusted): 1960M01 2013M03
Included observations: 639 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	51730.04	615.7437	84.01228	0.0000
@TREND	144.4909	0.867579	166.5450	0.0000
@MONTH=2	214.7869	778.4927	0.275901	0.7827
@MONTH=3	674.2405	778.4941	0.866083	0.3868
@MONTH=4	1476.381	782.1600	1.887569	0.0595
@MONTH=5	2010.607	782.1576	2.570590	0.0104
@MONTH=6	2482.814	782.1562	3.174320	0.0016
@MONTH=7	1426.984	782.1557	1.824424	0.0686
@MONTH=8	1446.229	782.1562	1.849028	0.0649
@MONTH=9	1941.945	782.1576	2.482806	0.0133
@MONTH=10	2282.907	782.1600	2.918721	0.0036
@MONTH=11	2355.756	782.1634	3.011846	0.0027
@MONTH=12	2278.605	782.1677	2.913192	0.0037

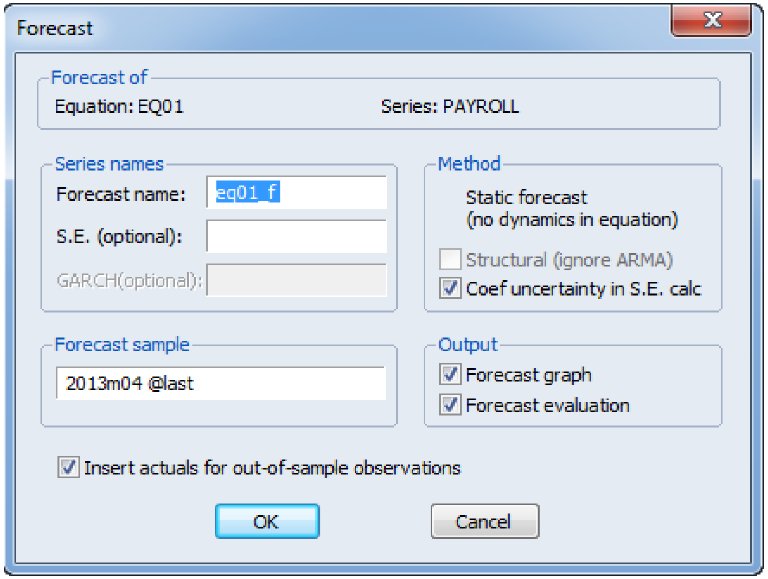
R-squared	0.977956	Mean dependent var	99366.01
Adjusted R-squared	0.977534	S.D. dependent var	26988.01
S.E. of regression	4045.164	Akaike info criterion	19.46857
Sum squared resid	1.02E+10	Schwarz criterion	19.55930
Log likelihood	-6207.207	Hannan-Quinn criter.	19.50379
F-statistic	2314.346	Durbin-Watson stat	0.006324
Prob(F-statistic)	0.000000		

Forecasting with Exogenous Variables: Example 1 (Part III)

- Now, let's produce a forecast for the ***payroll*** series based on our model.
- For this, all we have to do is press the ***Forecast*** button in the equation toolbar.

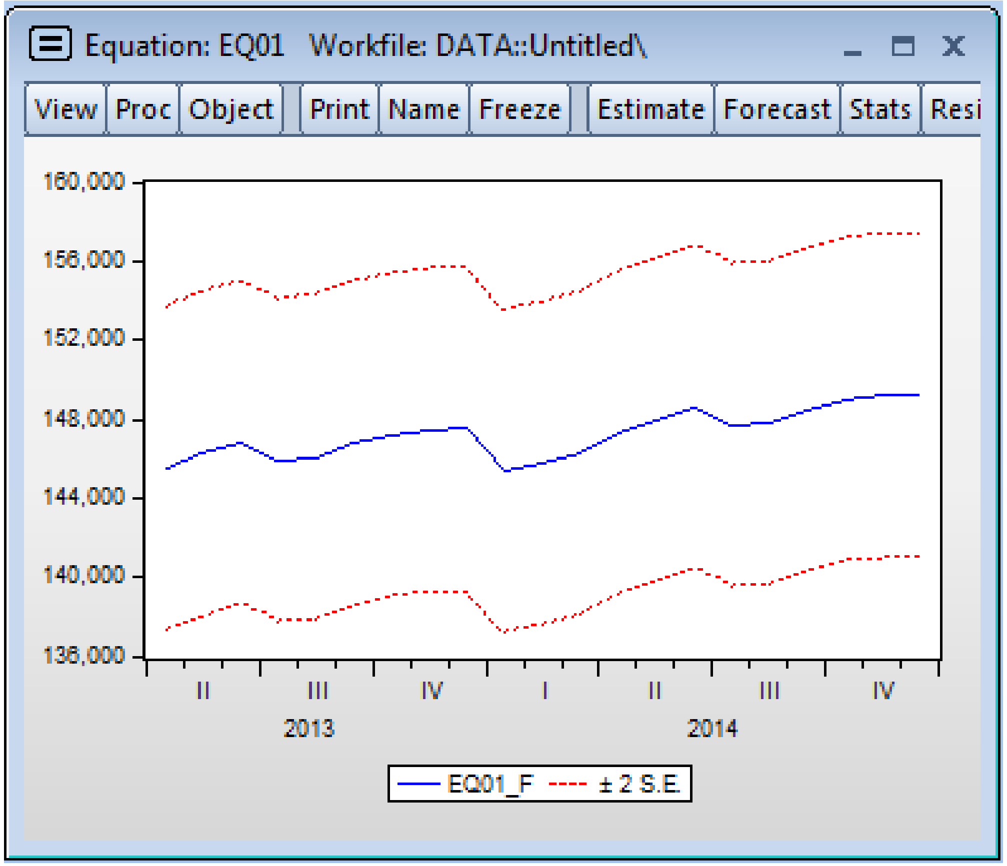
<u>**Example 1: Forecasting**</u>

1. On the equation box toolbar, press the ***Forecast*** button. The ***Forecast*** dialog box opens up.
2. Under ***Series name***, specify a name for the forecast series. EViews suggests a name (*payrollf*) but this series will be overwritten every time a new model is estimated. Let's save our series as ***eq01_f***.
3. Under ***Forecast sample***, select the sample over which the forecast will be carried out. Here we type, ***2013m04 @last.***
4. Check **Insert actuals for out-of-sample observations**.
5. Under ***Method***, notice that EViews indicates this is a **Static forecast (no dynamics in the equation)**. More details will be discussed later.
6. Under Output, check **Forecast graph** and **Forecast evaluation**. Click **OK**.



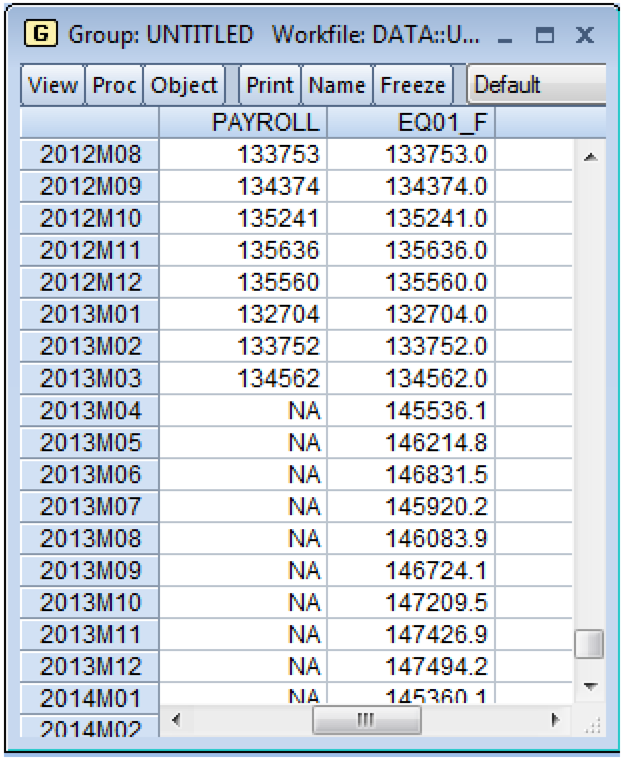
Forecasting with Exogenous Variables: Example 1 (Part IV)

- The *Forecast Output* is shown here. Notice that EViews shows the series ***eq01_f*** over the forecast sample, together with 2 standard error bands.



Forecasting with Exogenous Variables: Example 1 (Part V)

- Note also that there is now a new series ***eq01_f*** saved in the workfile. Let's open this series and the original ***payroll*** series as a group to inspect them more closely.
- Notice that the two series are identical when looking at the historical data. This is because we elected to check the box **Insert actuals for out-of-sample observations** which instructs EViews to use actual payroll data for the out-of-forecast sample.
- However, the ***eq01_f*** series contains actual forecasts of the payroll series for future periods. EViews computes these values employing the model.



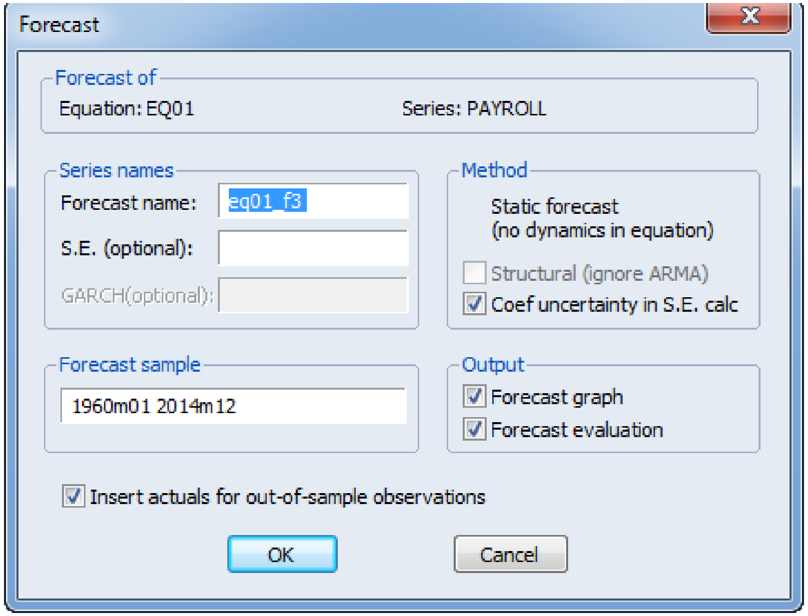
	PAYROLL	EQ01_F
2012M08	133753	133753.0
2012M09	134374	134374.0
2012M10	135241	135241.0
2012M11	135636	135636.0
2012M12	135560	135560.0
2013M01	132704	132704.0
2013M02	133752	133752.0
2013M03	134562	134562.0
2013M04	NA	145536.1
2013M05	NA	146214.8
2013M06	NA	146831.5
2013M07	NA	145920.2
2013M08	NA	146083.9
2013M09	NA	146724.1
2013M10	NA	147209.5
2013M11	NA	147426.9
2013M12	NA	147494.2
2014M01	NA	145360.1
2014M02		

Forecasting with Exogenous Variables: Example 1 (Part VI)

- What would happen if we set the forecast sample to be the entire range?

<u>**Example 1: Forecast Sample Changes**</u>

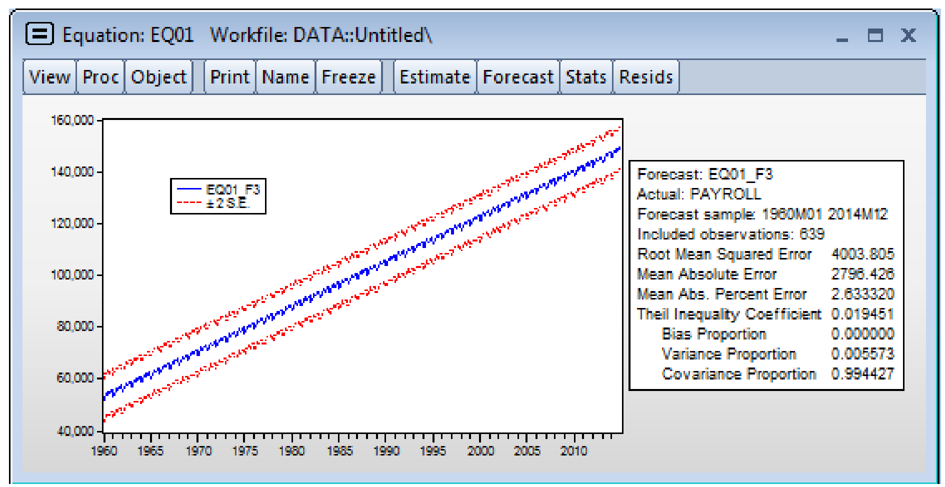
1. Open an ***equation*** and press the ***Forecast*** button. The ***Forecast*** dialog box opens up.
2. Under ***Series name,*** name the new forecasted series.
3. Set all the other options as we did before (check **Forecast graph** and **Forecast evaluation,** check **Insert actuals for out-of-sample observations**).
4. Under ***Forecast Sample***, set the sample to the entire workfile range (***1960m01 2014m12***). Click **OK**.



Forecasting with Exogenous Variables: Example 1 (Part VII)

- The *Forecast Output* is shown here. Notice that EViews has computed ***eq01_f3*** and the corresponding standard error bands over the entire sample. Notice also that, in addition to the graph, EViews has produced a small table: this is the ***Forecast Evaluation*** table.

- Although, we had checked the **Forecast evaluation** box in the previous illustrations, EViews was unable to produce an output when the forecast sample was set for future periods (*2013m04* to *2014m012*).
- This is because EViews could not check how well the forecasting model works since the ***payroll*** data beyond *2013m03* is missing. We would have to wait until a future date when ***payroll*** data becomes available in order to compare our forecasts with what actually happens.
- When we set the forecast sample to the entire workfile range (or a sample that includes actual historical data), it is possible to check for forecast accuracy. EViews compares the forecasted (predicted) values from the model (over the period *1960m01* to *2013m03*) to the actual data and computes the forecast evaluation table.



Forecasting with Exogenous Variables: In-Sample / Out-of-Sample Forecasts

- Notice that the *Forecast evaluation* in the previous example, simply compares the predicted values from the model to the actual data over the "historical" period (*1960m01* to *2013m03*).
- Note also that our model was estimated over the same period (*1960m01* to *2013m03*). In a sense, the "forecast" evaluation was carried out *in-sample* and not *out-of-sample*.
- In fact, since we don't have "actual" payroll data over the *2013m03* to *2014m12* period (the "true" forecast period), it is impossible for us to see how well our model performs *out-of-sample*. This is problematic because the history of forecasting is replete with cases when models work well *in-sample* but perform extremely poorly *out-of-sample*.
- A common practice to address this issue is to reserve part of the data by not including it in the estimation sample, effectively pretending that the history ends sooner and the reserved data is part of the future (part of forecasts).
- We can then produce forecasts over the reserved sample and perform forecast evaluation by comparing the *out-of-sample* forecast values to the actual history.

Forecasting with Exogenous Variables: Example 2 (Part I)

- Let's carry out ***Example 1*** by breaking down the sample as follows:
  - ✓ **<u>Estimation Sample:</u>** *1960m01* to *2008m12*
  - ✓ **<u>Forecast Sample:</u>** *2009m1* to *2014m12*
- At first, one should adjust the model estimation performed in ***Example 1***.

Equation: EQ02 Workfile: RESULTS::Untitled\

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: PAYROLL
Method: Least Squares
Date: 05/18/13 Time: 03:29
Sample: 1960M01 2008M12
Included observations: 588

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	49929.74	351.5773	142.0164	0.0000
@TREND	154.2915	0.537060	287.2889	0.0000
@MONTH=2	180.2595	446.5039	0.403713	0.6866
@MONTH=3	623.8864	446.5049	1.397267	0.1629
@MONTH=4	1219.126	446.5065	2.730365	0.0065
@MONTH=5	1740.161	446.5088	3.897260	0.0001
@MONTH=6	2237.318	446.5117	5.010660	0.0000
@MONTH=7	1207.496	446.5152	2.704266	0.0070
@MONTH=8	1218.041	446.5194	2.727857	0.0066
@MONTH=9	1710.933	446.5243	3.831669	0.0001
@MONTH=10	2013.172	446.5297	4.508484	0.0000
@MONTH=11	2071.942	446.5359	4.640035	0.0000
@MONTH=12	2012.691	446.5427	4.507277	0.0000

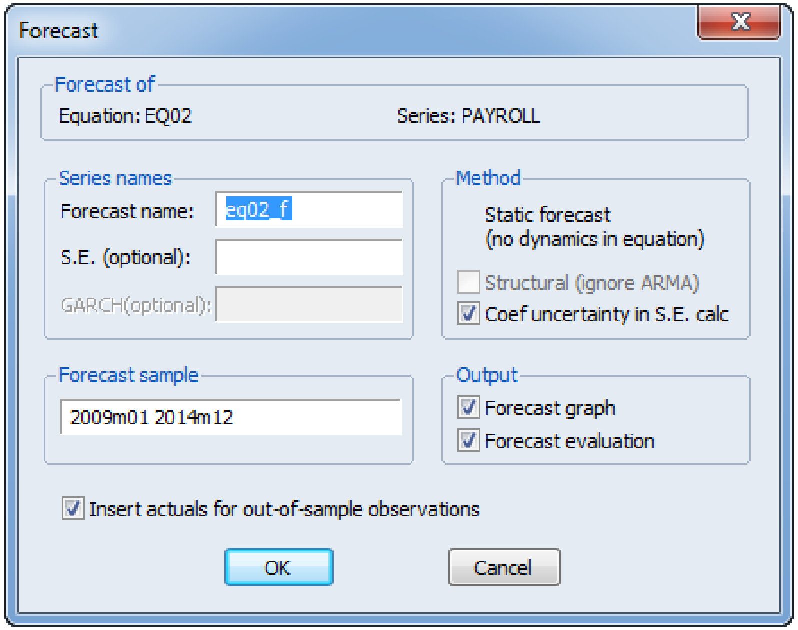
R-squared	0.993096	Mean dependent var	96567.22
Adjusted R-squared	0.992952	S.D. dependent var	26324.79
S.E. of regression	2210.080	Akaike info criterion	18.26131
Sum squared resid	2.81E+09	Schwarz criterion	18.35807
Log likelihood	-5355.824	Hannan-Quinn criter.	18.29901
F-statistic	6892.264	Durbin-Watson stat	0.019212
Prob(F-statistic)	0.000000		

Forecasting with Exogenous Variables: Example 2 (Part II)

- Now, let's produce a forecast for the ***payroll*** series using the forecast sample.

<u>**Example 2: Forecasting**</u>

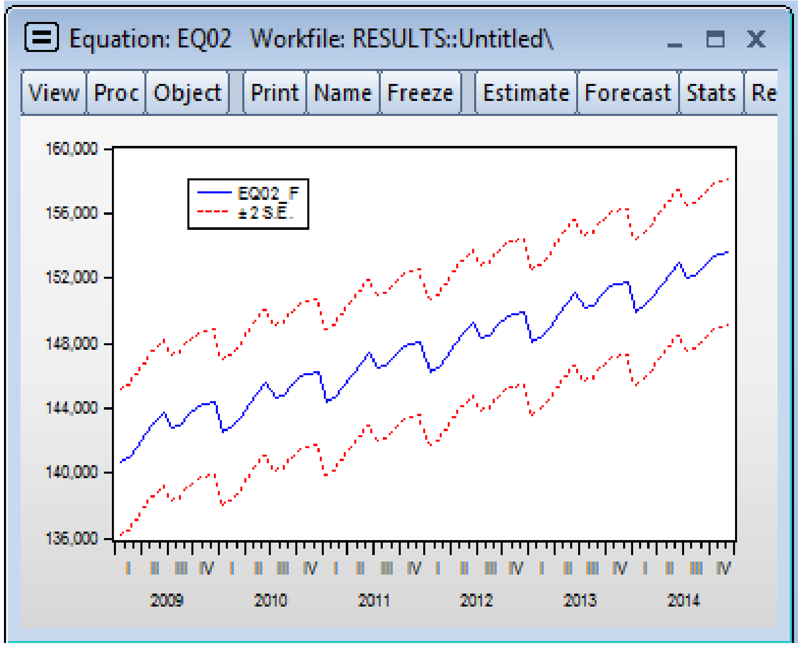
1. On the equation box toolbar, press the ***Forecast*** button. The ***Forecast*** dialog box opens up.
2. Under ***Series name*,** name the series.
3. Under the ***Forecast sample***, type the forecast sample (here, ***2009m1 2014m12***)***.***
4. Set all the other options as we did previously (check **Forecast graph, Forecast evaluation,** and **Insert actuals for out-of-sample observations**). Click **OK**.



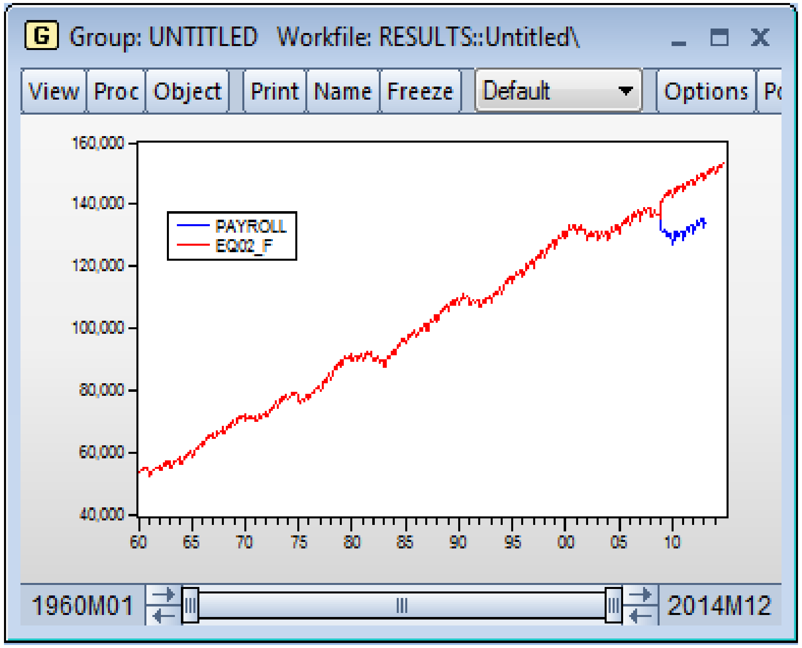
Forecasting with Exogenous Variables: Example 2 (Part III)

- The *Forecast Output* is shown here (note that we have removed the forecast evaluation table, which we discuss next). For comparison purposes, we have also shown a graph of the ***payroll*** and ***eq02_f*** series. Notice that since we selected to **Insert actuals for out-of-sample observations** the series are identical over the estimation sample.

Forecast Graph



Payroll vs. eq02_f



Forecasting with Exogenous Variables: Example 2 (Part IV)

- Let us describe the *Forecast Evaluation* Table displayed here.

Forecast: EQ02_F	
Actual: PAYROLL	
Forecast sample: 2009M01 2014M12	
Included observations: 51	
Root Mean Squared Error	14243.17
Mean Absolute Error	14165.08
Mean Abs. Percent Error	10.76371
Theil Inequality Coefficient	0.051333
Bias Proportion	0.989065
Variance Proportion	0.001134
Covariance Proportion	0.009801

Forecast Evaluation (Part I):

- ✓ First, notice that the forecast evaluation is saved in two formats. If you check the box (**Forecast graph**), the forecast evaluation table is included along with the forecast graph (the first table shown here is copied from this option). If you uncheck **Forecast graph**, the **Forecast evaluation** is shown in a separate table (the second table shown here).
- ✓ EViews indicates the number of observations used to perform the forecast evaluation. Here we have 51 periods, which span the period from *2009m01* to *2013m03*. Note that for the remaining period (*2013m03* to *2014m12*), EViews does not carry out a forecast evaluation because the values of the dependent variable (***payroll***) are missing.

Equation: EQ02 Workfile: RESULTS::Untitl...

View | Proc | Object | Print | Name | Freeze | Estimate | Forecas

Forecast Evaluation

Forecast: EQ02_F	
Actual: PAYROLL	
Forecast sample: 2009M01 2014M12	
Included observations: 51	
Root Mean Squared Error	14243.17
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Forecasting with Exogenous Variables: Example 2 (Part V)

Forecast Evaluation (Part II)

The reported forecast statistics indicate that our forecasting model does not perform well out-of-sample.

- ✓ The **Root Mean Squared Error** (*RMSE*) is the standard deviation of the forecast errors. This is quite large when compared to the standard deviation of ***payroll*** series.
- ✓ Note that **RMSE** and **Mean Absolute Error** depend on the scale of the dependent variable, while the next two statistics (**Mean Abs. Percent Error** and **Theil Inequality Coefficient**) are scale invariant. The *Theil Coefficient* lies between 0 and 1, with 0 indicating a perfect fit.
  - **Bias Proportion** indicates how far is the mean of the forecast from the mean of the actual series.
  - **Variance Proportion** indicates how far is the variance of the forecasts from the variance of the actual series.
  - **Covariance Proportion** measures the remaining unsystematic forecasting errors.
  - If the forecasts are "good" the bias and variance proportions should be small (which is not the case here).
  - Note that the Bias, Variance and Covariance Proportions add up to 1 (they are given as proportions out of 1).

Forecast: EQ02_F
Actual: PAYROLL
Forecast sample: 2009M01 2014M12
Included observations: 51

Root Mean Squared Error	14243.17
Mean Absolute Error	14165.08
Mean Abs. Percent Error	10.76371
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Equation: EQ02 Workfile: RESULTS::Untitl...

View | Proc | Object | Print | Name | Freeze | Estimate | Forecas

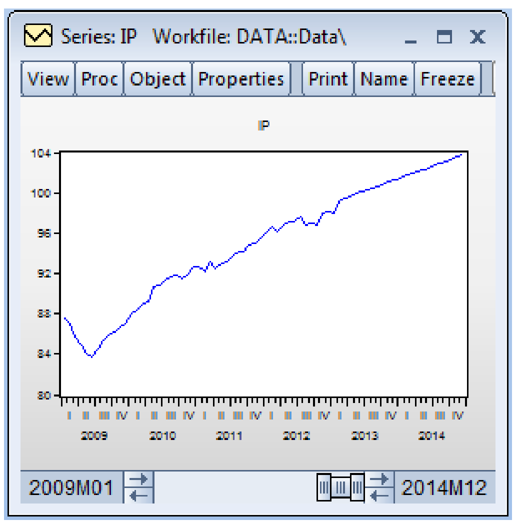
Forecast Evaluation

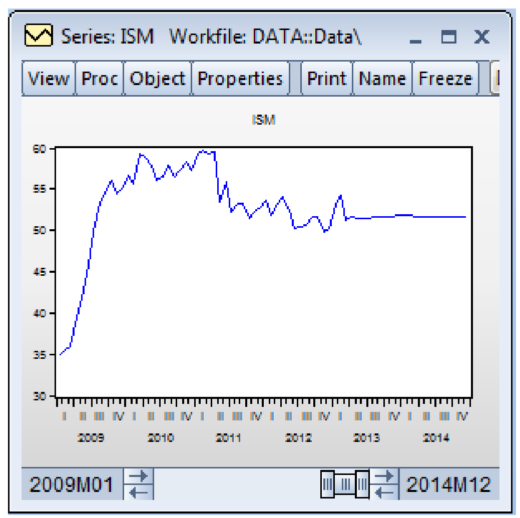
Forecast: EQ02_F
Actual: PAYROLL
Forecast sample: 2009M01 2014M12
Included observations: 51

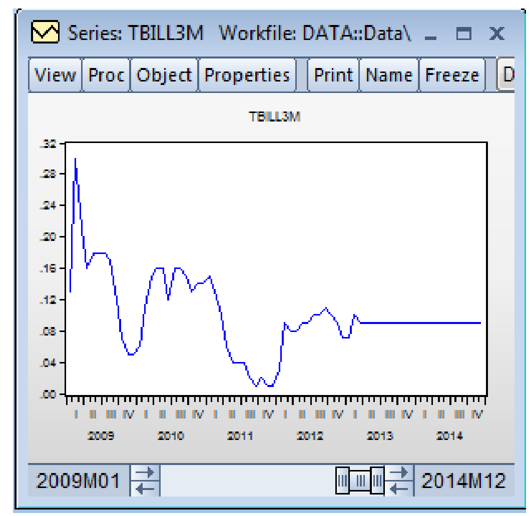
Root Mean Squared Error	14243.17
Mean Absolute Error	14165.08
Mean Absolute Percentage Error	10.76371
Theil Inequality Coefficient	0.051333
Bias Proportion	0.989065
Variance Proportion	0.001134
Covariance Proportion	0.009801

Forecasting with Exogenous Variables: Example 3 (Part I)

- In order to be able to produce an *out-of-sample* forecast, we need to know the future values for all explanatory variables. In this case, it was easy enough so far, because we used ***@trend*** and seasonal factors to forecast our dependent variable. EViews easily produces "forecasts" for trend variable and seasonal factors.
- However, for most explanatory variables, we need to provide values over the forecast period. For example, suppose we want to forecast ***payroll*** using ***ip***, ***ism*** and ***tbill3m*** as additional explanatory variables. As shown previously (and in the graphs below), we have provided data for the explanatory variables over the forecast period.







Forecasting with Exogenous Variables: Example 3 (Part II)

- Let’s define the sample objects by typing in the command window:

```
sample sample_est @first 2008m12
sample sample_for 2009m01 @last
```

Example 3: Estimation

1. Type in the command window:

EViews

File Edit Object View Proc Quick Options Add-ins W

```
smpl sample_est
ls payroll c ip ism tbill3m @trend @expand(@month,@droplast)
```

Equation: EQ03 Workfile: RESULTS::Untitled\

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: PAYROLL
Method: Least Squares
Date: 05/18/13 Time: 03:51
Sample: 1960M01 2008M12
Included observations: 588

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	46247.71	780.3023	59.26898	0.0000
IP	315.6302	17.77020	17.76177	0.0000
ISM	-39.48883	11.44827	-3.449326	0.0006
TBILL3M	259.7414	28.10514	9.241776	0.0000
@TREND	113.5073	2.356990	48.15775	0.0000
@MONTH=1	-2055.488	354.9367	-5.791140	0.0000
@MONTH=2	-1888.549	354.9575	-5.320493	0.0000
@MONTH=3	-1457.196	354.9266	-4.105626	0.0000
@MONTH=4	-837.5068	354.9124	-2.359756	0.0186
@MONTH=5	-323.2735	354.9157	-0.910846	0.3628
@MONTH=6	197.4716	354.9057	0.556406	0.5782
@MONTH=7	-838.4017	354.8982	-2.362372	0.0185
@MONTH=8	-832.2146	354.9055	-2.344891	0.0194
@MONTH=9	-300.5624	354.8907	-0.846915	0.3974
@MONTH=10	2.720788	354.8861	0.007667	0.9939
@MONTH=11	50.96002	354.8917	0.143593	0.8859

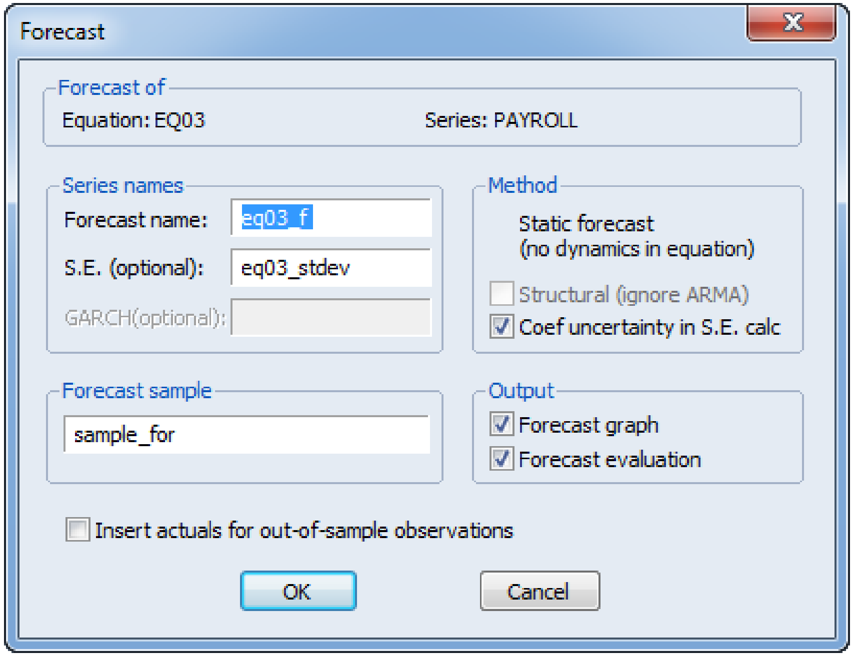
R-squared	0.995661	Mean dependent var	96567.22
Adjusted R-squared	0.995547	S.D. dependent var	26324.79
S.E. of regression	1756.590	Akaike info criterion	17.80697
Sum squared resid	1.76E+09	Schwarz criterion	17.92606
Log likelihood	-5219.249	Hannan-Quinn criter.	17.85337
F-statistic	8750.800	Durbin-Watson stat	0.028888
Prob(F-statistic)	0.000000		

Forecasting with Exogenous Variables: Example 3 (Part III)

- Now, let's produce a forecast for the ***payroll*** series with this model.

Example 3: Forecasting

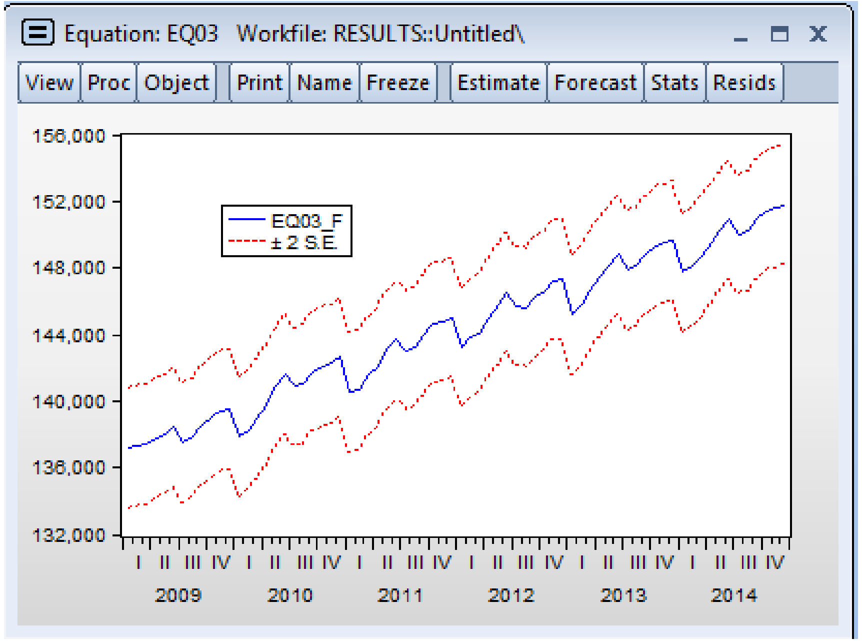
1. Open ***eq03***. On the equation box toolbar, press the ***Forecast*** button. The ***Forecast*** dialog box opens up.
2. Under ***Series names*****,** type the name of the forecasted series ***eq03_f*** in the **Forecast name** field.
3. Under ***Series names***, **S.E. (optional)** field, type the name of standard errors series. This creates and saves a new series ***eq03_stdev***.
4. Under ***Forecast sample***, type the forecast sample ***sample_for***.
5. Set all the other options as follows: check **Forecast graph**, **Forecast evaluation,** and uncheck **Insert actuals for out-of-sample observations**. Click **OK**.



Forecasting with Exogenous Variables: Example 3 (Part IV)

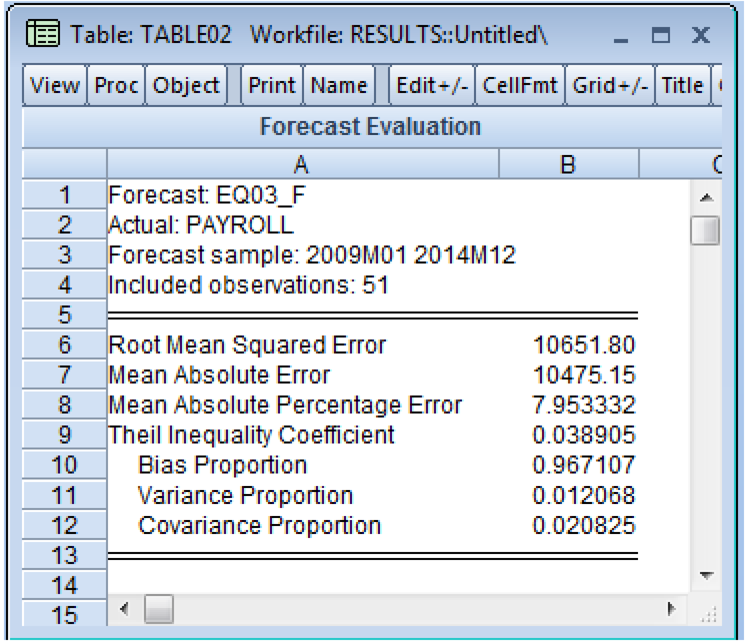
- The *Forecast Output* is shown here (note that we have removed the forecast evaluation table, which we discuss below).

Forecast Graph



Forecasting with Exogenous Variables: Example 3 (Part V)

- The *Forecast Evaluation* output from this model is shown here. As you can see, the Bias Proportion is still large, indicating that the forecast is not “very good.”
- Nonetheless, this model performs considerably better than the previous one (*RMSE* is lower, the *Mean Absolute Percentage Error* is lower, and even the *Bias Proportion* is lower).



	A	B
1	Forecast: EQ03_F	
2	Actual: PAYROLL	
3	Forecast sample: 2009M01 2014M12	
4	Included observations: 51	
5		
6	Root Mean Squared Error	10651.80
7	Mean Absolute Error	10475.15
8	Mean Absolute Percentage Error	7.953332
9	Theil Inequality Coefficient	0.038905
10	Bias Proportion	0.967107
11	Variance Proportion	0.012068
12	Covariance Proportion	0.020825
13		
14		
15		

EViews: Introductory User Guide

BASIC FORECASTING: FORECASTING USING LAGGED DEPENDENT VARIABLES

Forecasting with Lagged Dependent Variables

- Oftentimes, time series models used for forecasting include a lagged dependent variable.
- The presence of a lagged dependent variable complicates forecasting because there is an issue as to how to evaluate the dependent variable that appears on the right-hand side of the equation.
- EViews offers two ways to deal with lagged dependent variables:
  - ✓ **Dynamic Forecasting**
  - ✓ **Static Forecasting**
- Dynamic forecasting uses the forecasted value of the lagged dependent variable.
- Static forecasting uses the actual value of the lagged dependent variable.
- For out of sample forecasting, dynamic forecasting is usually the only possible approach (due to the lack of actual data, static forecasting is impossible).

Forecasting with Lagged Dependent Variables: Example 4 (Part I)

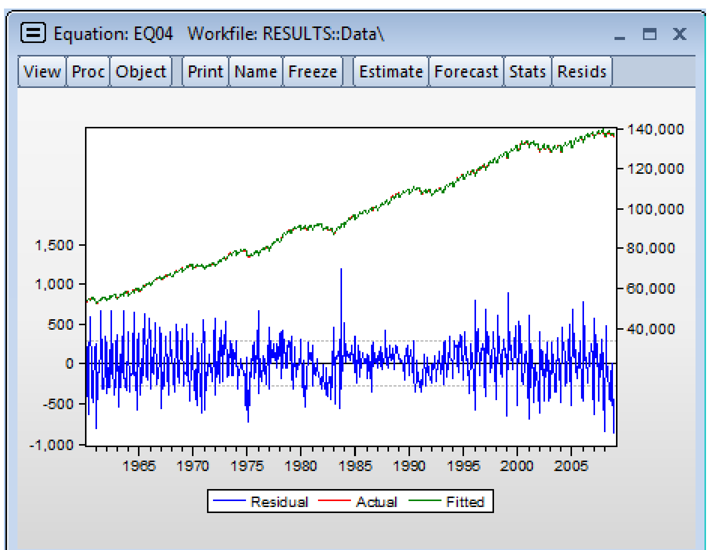
Example 4: Estimation

1. Let's first specify a model with lagged dependent variable on the right-hand side of the equation. Type in the command window:

EViews

File Edit Object View Proc Quick Options Add-ins Window

```
smpl sample_est
ls payroll c payroll(-1) payroll(-2) @trend @expand(@month, @droplast)
```



Equation: EQ04 Workfile: RESULTS::Data\

View Proc Object Print Name Freeze Estimate Forecast Stats Resids

Dependent Variable: PAYROLL
Method: Least Squares
Date: 05/16/13 Time: 15:13
Sample (adjusted): 1960M03 2008M12
Included observations: 586 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	350.6336	285.8700	1.226549	0.2205
PAYROLL(-1)	1.313667	0.040186	32.68988	0.0000
PAYROLL(-2)	-0.319591	0.040372	-7.916247	0.0000
@TREND	0.858637	0.847096	1.013624	0.3112
@MONTH=1	-2146.080	57.94138	-37.03882	0.0000
@MONTH=2	967.4137	108.8173	8.890259	0.0000
@MONTH=3	452.3463	58.72441	7.702868	0.0000
@MONTH=4	522.4720	60.29956	8.664607	0.0000
@MONTH=5	403.3954	61.79192	6.528287	0.0000
@MONTH=6	406.3747	60.54366	6.712094	0.0000
@MONTH=7	-1109.973	60.14951	-18.45357	0.0000
@MONTH=8	412.3580	72.24708	5.707608	0.0000
@MONTH=9	562.3306	57.71580	9.743096	0.0000
@MONTH=10	220.4988	60.21070	3.662121	0.0003
@MONTH=11	39.80625	58.34976	0.682201	0.4954

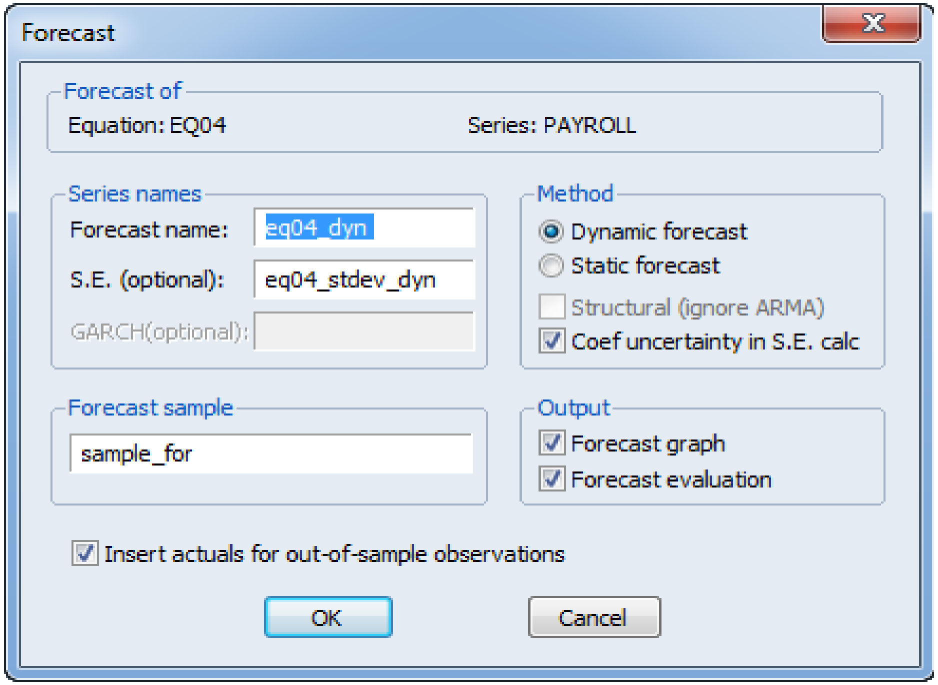
R-squared	0.999885	Mean dependent var	96714.42
Adjusted R-squared	0.999882	S.D. dependent var	26248.47
S.E. of regression	284.6586	Akaike info criterion	14.16572
Sum squared resid	46268440	Schwarz criterion	14.27767
Log likelihood	-4135.557	Hannan-Quinn criter.	14.20935
F-statistic	355252.4	Durbin-Watson stat	1.955294
Prob(F-statistic)	0.000000		

Forecasting with Lagged Dependent Variables: Example 4 (Part II)

- Now, let's produce a *Dynamic Forecast* for the ***payroll*** based on our model.

<u>**Example 4: Dynamic Forecast**</u>

1. On the equation box toolbar, press the ***Forecast*** button. The ***Forecast*** dialog box opens up.
2. Under ***Series names***, name the series ***eq04_dyn*** in **Forecast name** field. Under **S.E. (optional)** field, type the name of standard errors series ***eq04_stdev_dyn***.
3. Under ***Forecast sample***, type the forecast sample ***sample_for***. Set all the other options as follows: check **Forecast graph**, **Forecast evaluation**, and check **Insert actuals for out-of-sample observations**.
4. Notice that under ***Method***, you now can choose between **Dynamic Forecast** and **Static Forecast**. Let's choose **Dynamic Forecast** here. Click **OK**.

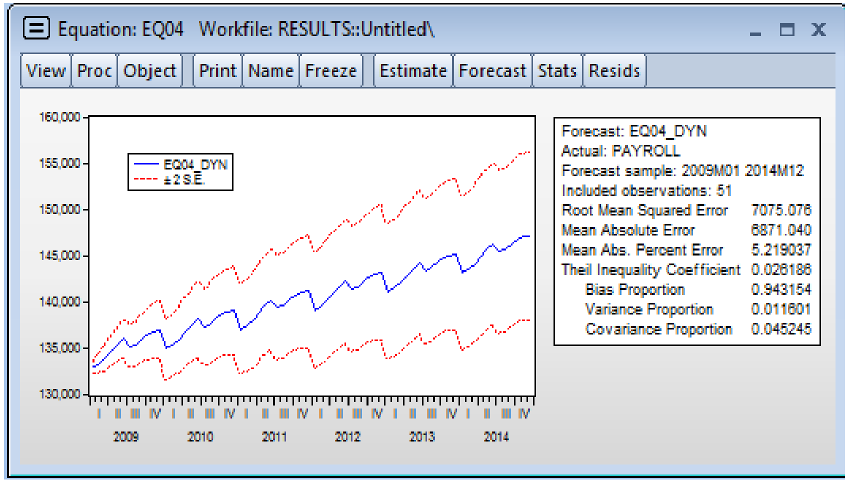


Forecasting with Lagged Dependent Variables: Example 4 (Part III)

- The *Forecast Output* is shown here. Notice that EViews produces forecast values for payroll series over the entire forecast sample: *2009m1 to 2014m12*.

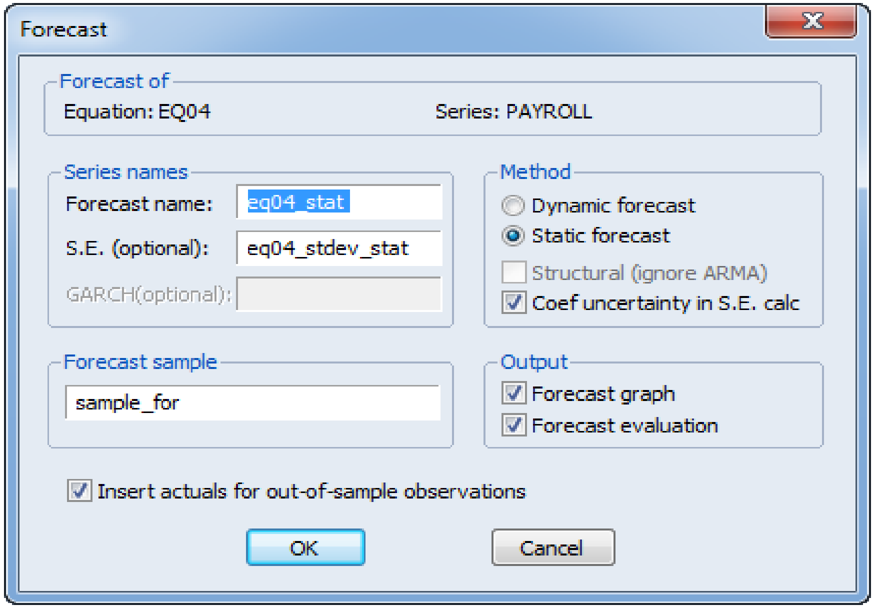
How are Dynamic Forecasts Performed?

- You can see that the confidence error bands widen dramatically towards the end of the forecast sample. This is because dynamic forecasting uses the forecast values of the lagged dependent variables. The forecast errors tend to compound over time resulting in larger error bands the further out we are in the forecast sample.
- The first forecasted value (*2009m01*) uses the actual value of *2008m12* (***payroll(-1)***) and the actual value of *2008m11* (***payroll (-2)***).
- The second forecasted value (*2009m02*) uses the forecasted value of *2009m01* (***payroll (-1)***; estimated previously) and the actual value of *2008m12* (***payroll(-2)***).
- The third forecasted value (*2009m03*) uses the forecasted value of *2009m02* (***payroll (-1);*** estimated in step 2) and the forecasted value of ***2009m01*** (***payroll(-2);*** estimated in step 1).



Forecasting with Lagged Dependent Variables: Example 4 (Part IV)

- Let's now produce a *Static Forecast* of the ***payroll*** based on the same model.



Example 4: Static Forecast

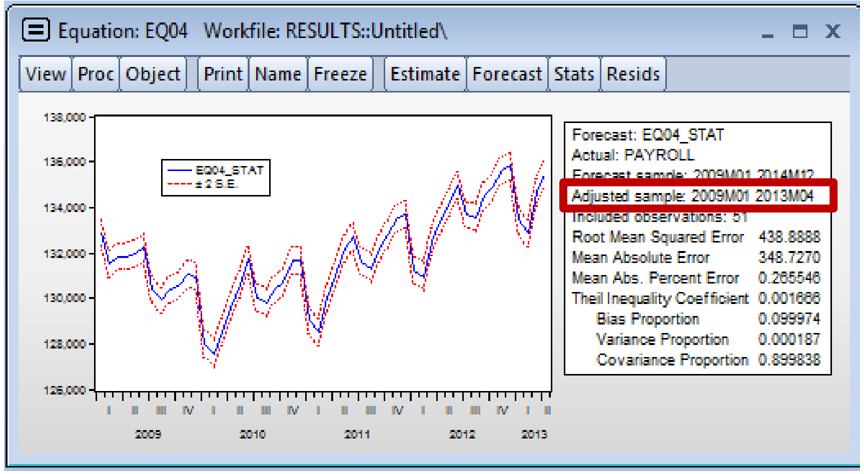
1. Open an ***equation***. Follow steps 1-3 as in the previous example (naming the forecast series ***eq04_stat*** and its standard deviation ***eq04_stdev_stat***).
2. Under ***Method***, select **Static Forecast**.
3. Click **OK**.

Forecasting with Lagged Dependent Variables: Example 4 (Part V)

- The *Forecast Output* is shown here.

<u>How are Static Forecasts Performed?</u>

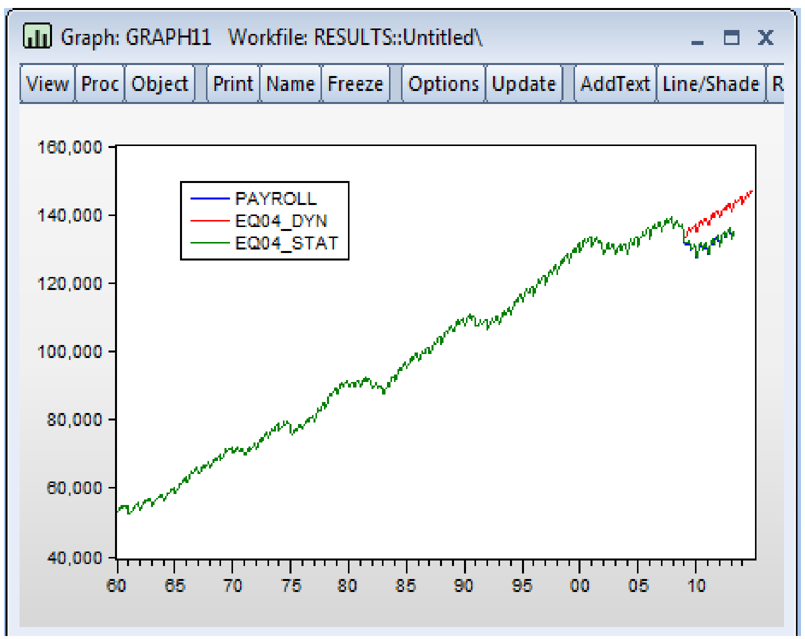
- ❑ First, notice that the forecast sample is adjusted to include the period only from *2009m01* to *2013m04* and not the entire forecast sample (to *2014m12*).
- ❑ This is because static forecasts are one-step ahead forecasts only. They use actual values of lagged dependent variables in order to perform the forecast. Since we have actual data for ***payroll*** series only up until *2013m03*, EViews can only produce forecasts for the period from *2009m01* to *2013m04* .
- ❑ The first forecasted value (*2009m01*) uses the actual value of *2008m12* (***payroll(-1)***) and the actual value of *2009m11* (***payroll (-2)***).
- ❑ The second forecasted value (*2009m02*) uses the actual value of *2009m01* (***payroll (-1)***) and the actual value of *2008m12* (***payroll(-2)***).
- ❑ The third forecasted value (*2009m03*) uses the actual value of *2009m02* (***payroll (-1)***) and the actual value of *2009m01* (***payroll(-2)***).

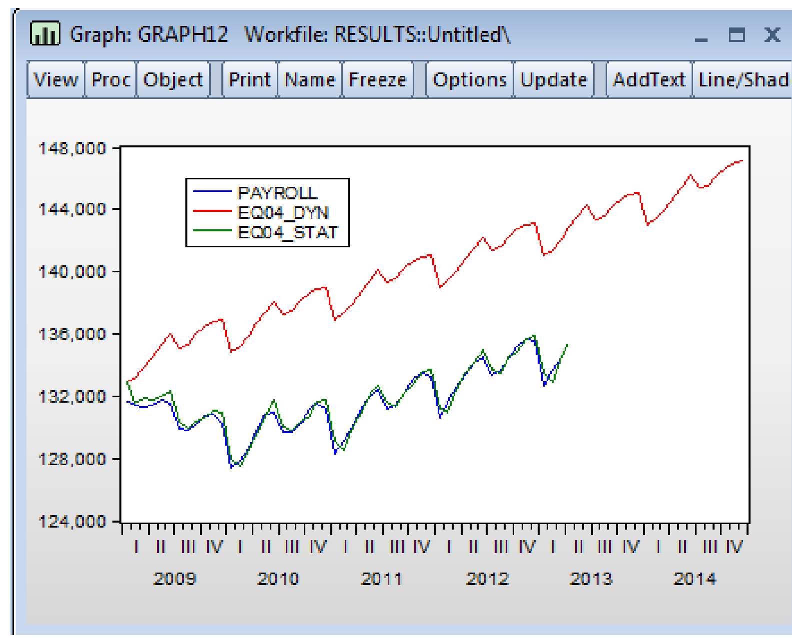


Forecasting with Lagged Dependent Variables: Example 4 (Part VI)

- Let us compare the two forecasts more directly. For this, open series ***payroll***, ***eq04_dyn*** and ***eq94_stat*** as a group and plot the series against each other.

❑ The static forecast performs much better than the dynamic forecast because it uses actual instead of the forecasted lagged values over the forecast period. The historical values are the same because we checked **Insert actuals for out-of-sample observations** in both cases.





EViews: Introductory User Guide

BASIC FORECASTING: FORECASTING USING ARMA ERRORS

Forecasting with AR terms: Example 5 (Part I)

- Models with ARMA terms are also widely used in forecasting. The presence ARMA terms involve some additional complexities in forecasting, which we highlight here.

Example 5: Estimation with AR terms

1. Let's first specify a model with two AR terms. Type in the command window:

EViews

File Edit Object View Proc Quick Options Add-ins

```
smpl sample_est
ls payroll c ar(1) ar(2) @trend @expand(@month, @droplast)
```

Equation: EQ06 Workfile: RESULTS::Data\

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: PAYROLL
Method: Least Squares
Date: 05/16/13 Time: 18:35
Sample (adjusted): 1960M03 2008M12
Included observations: 586 after adjustments
Convergence achieved after 6 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	53731.74	5812.165	9.244704	0.0000
@TREND	144.9469	14.68585	9.869836	0.0000
@MONTH=1	-2224.625	39.83555	-55.84522	0.0000
@MONTH=2	-2020.431	61.43612	-32.88670	0.0000
@MONTH=3	-1556.285	75.62571	-20.57878	0.0000
@MONTH=4	-941.6838	84.65292	-11.12406	0.0000
@MONTH=5	-401.7163	89.68691	-4.479097	0.0000
@MONTH=6	114.1796	91.27033	1.251004	0.2114
@MONTH=7	-897.0218	89.55955	-10.01592	0.0000
@MONTH=8	-867.9483	84.39099	-10.28485	0.0000
@MONTH=9	-356.6119	75.22939	-4.740327	0.0000
@MONTH=10	-36.00929	60.97680	-0.590541	0.5551
@MONTH=11	41.04470	39.50188	1.039057	0.2992
AR(1)	1.313667	0.040186	32.68988	0.0000
AR(2)	-0.319591	0.040372	-7.916247	0.0000

R-squared	0.999885	Mean dependent var	96714.42
Adjusted R-squared	0.999882	S.D. dependent var	26248.47
S.E. of regression	284.6586	Akaike info criterion	14.16572
Sum squared resid	46268440	Schwarz criterion	14.27767
Log likelihood	-4135.557	Hannan-Quinn criter.	14.20935
F-statistic	355252.4	Durbin-Watson stat	1.955294
Prob(F-statistic)	0.000000		

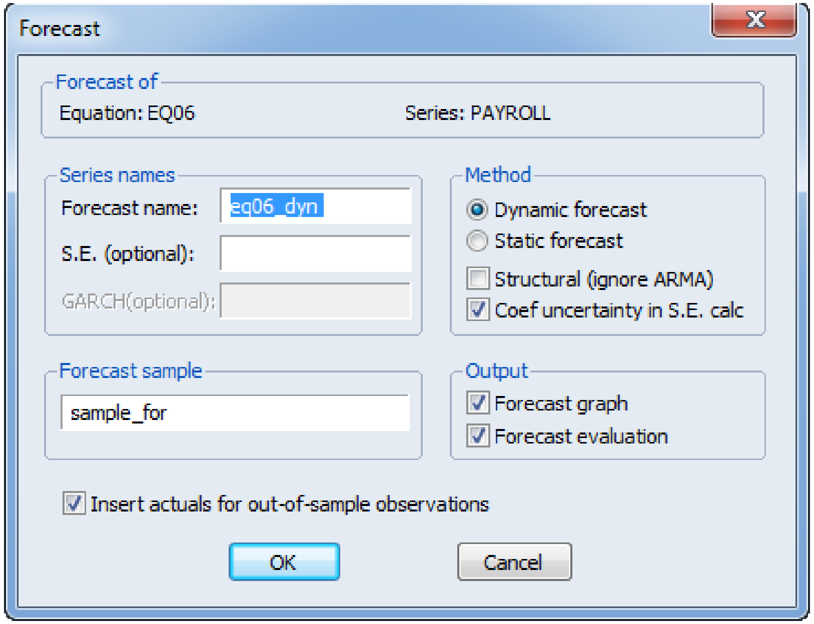
Inverted AR Roots	.99	.32

Forecasting with AR terms: Example 5 (Part II)

- Let's produce *dynamic* and *static* forecast for the *AR(2)* model we estimated.

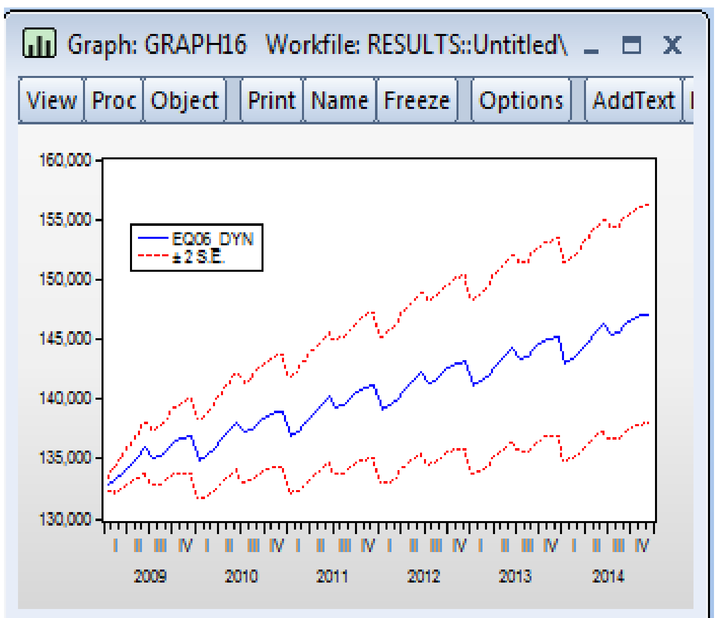
<u>**Example 5: Forecasting with AR terms**</u>

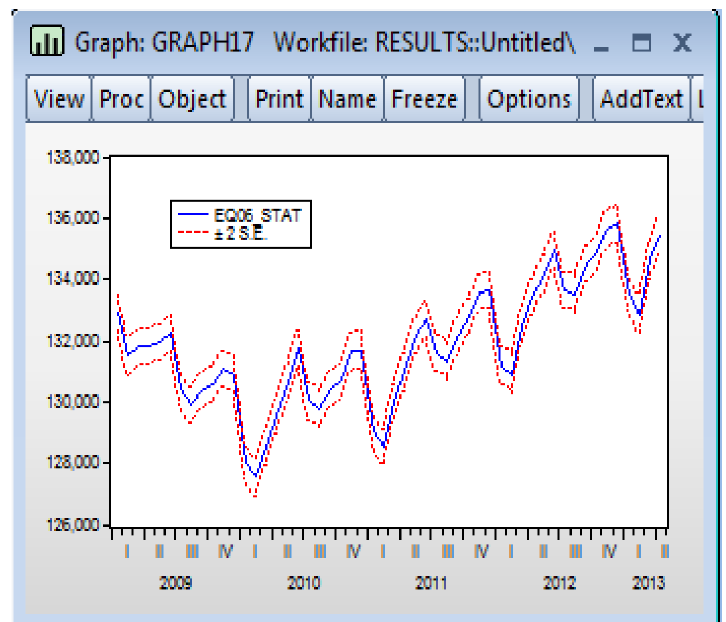
1. Open an ***equation*** and click the ***Forecast*** button. As usual, the ***Forecast*** dialog box opens up. Name the series ***eq06_dyn*** for the dynamic series and ***eq06_stat*** for the static forecast series.
2. Under ***Forecast Sample*** set the sample to ***sample_for*** (see ***Example 3***, ***Part II***). Under ***Method***, select **Dynamic forecast** (for the dynamic series), and **Static forecast** (for the static series). Set the rest of the parameters as shown here. Click **OK**.



Forecasting with AR terms: Example 5 (Part III)

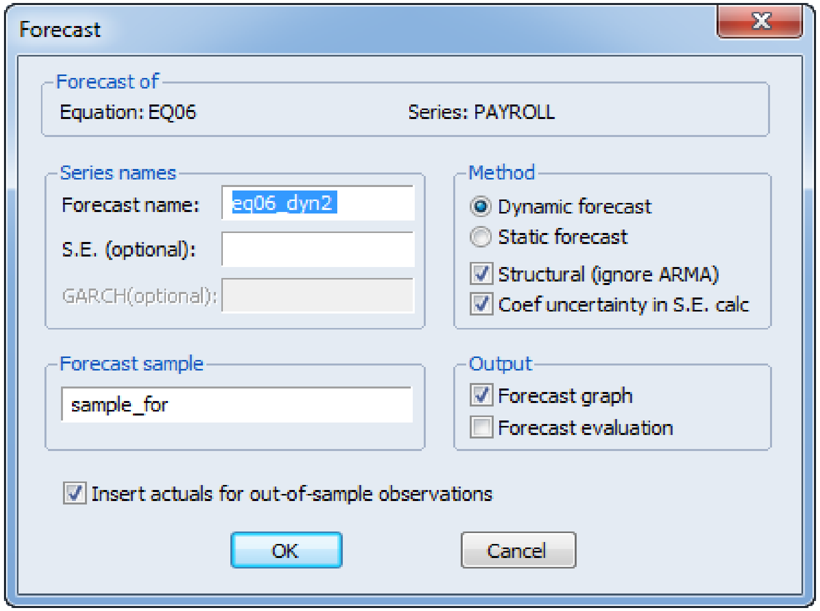
- The *Forecast Output* for both methods is shown here. To produce forecasts with *AR* terms, EViews adds forecasts of the residuals to the forecasts of the structural model (structural model is based solely on explanatory variables). As expected, the static forecast (bottom graph) goes up to *2013m04*, and performs better than the dynamic forecast.
- In the dynamic forecast (top graph), the lagged residuals are forecasted dynamically. This means that future values of lagged residuals are formed using the forecasted values of the dependent variable. In contrast, the static forecast uses actual lagged residuals and actual values for the dependent variable to produce forecasts.





Forecasting with AR terms: Example 5 (Part IV)

- There are cases when you may wish to assume that the ARMA errors are zero.
- For this, we can select the **Structural (ignore ARMA)** box under ***Method***.

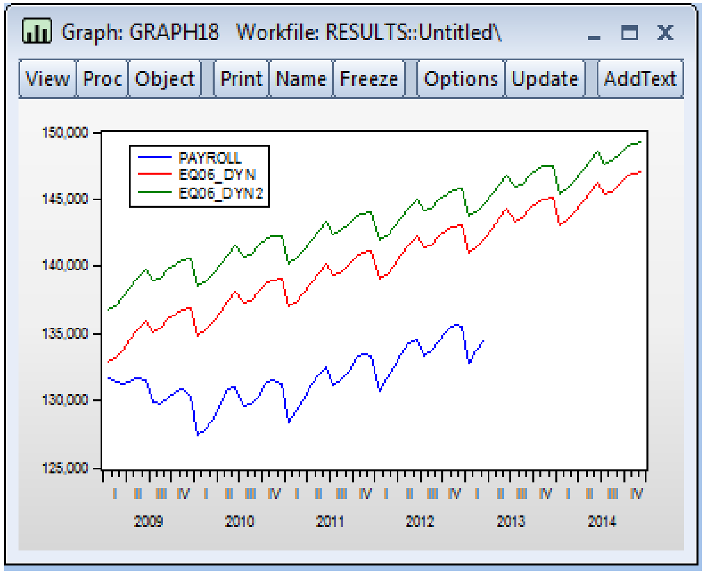


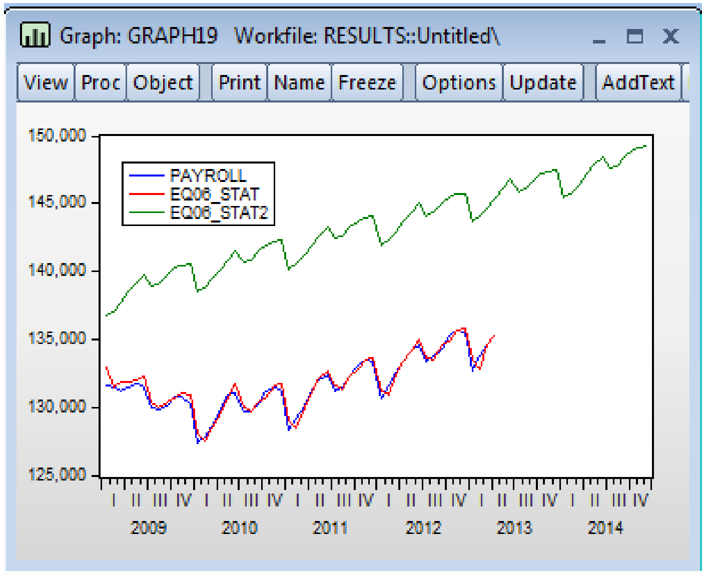
<u>**Example 5: Forecasting with AR terms**</u>

1. Open an ***equation*** and click the ***Forecast*** button. As usual, the ***Forecast*** dialog box opens up. Name the series ***eq06_dyn2*** for the dynamic series and ***eq06_stat2*** for the static forecast series.
2. Under ***Forecast Sample*** set the sample to ***sample_for.*** Under ***Method***, select **Dynamic forecast** (for the dynamic series), and **Static forecast** (for the static series). Set the rest of the parameters as shown here.
3. Check **Structure (ignore ARMA)** box under ***Method***. Click **OK**.

Forecasting with AR terms: Example 5 (Part V)

- The graphs shown here plot the forecasted values for both methods (dynamic and static) when ARMA terms are included (***eq06_dyn*** or ***eq06_stat***) or ignored (***eq06_dyn2*** or ***eq06_stat2***).
- First, it is important to note that the static and dynamic forecasts obtained by ignoring ARMA terms are identical (you can see this by plotting ***eq06_dyn2*** against ***eq06_stat2***; not shown here). This is expected, since static and dynamic forecasts differ only if there are lagged dependent variables or ARMA terms. If we choose to ignore the ARMA terms, there are no differences between the two. Note also that the static forecasts when ARMA terms are ignored are provided for the entire forecast period (bottom graph). This was possible since we know the values of all exogenous variables over the entire forecast sample.
- For both dynamic and static forecasts, ignoring ARMA terms produces "worse" forecasts than when ARMA terms are included.





Forecasting with MA terms: Example 6 (Part I)

- It is just as easy in EViews to produce forecasts from models with MA errors.

Example 6: Estimation with MA terms

1. Let's first specify a model with one MA term. Type in the command window:

```
EViews
File  Edit  Object  View  Proc  Quick  Options  Add-ins  Window
smpl sample_est
ls payroll c ar(1) ar(2) payroll(-1) @trend @expand(@month, @droplast)
```

Equation: EQ08 Workfile: RESULTS::Data\

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: PAYROLL
Method: Least Squares
Date: 05/16/13 Time: 21:04
Sample: 1960M01 2008M12
Included observations: 588
Convergence achieved after 19 iterations
MA Backcast: 1959M12

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	51959.63	285.7438	181.8400	0.0000
@TREND	154.2556	0.558085	276.4018	0.0000
@MONTH=1	-2119.135	233.1706	-9.088345	0.0000
@MONTH=2	-1839.254	328.5032	-5.598892	0.0000
@MONTH=3	-1395.590	328.4956	-4.248428	0.0000
@MONTH=4	-800.3147	328.4872	-2.436365	0.0151
@MONTH=5	-279.2437	328.4813	-0.850105	0.3956
@MONTH=6	217.9496	328.4750	0.663520	0.5073
@MONTH=7	-811.8366	328.4708	-2.471564	0.0137
@MONTH=8	-801.2555	328.4665	-2.439383	0.0150
@MONTH=9	-308.3274	328.4641	-0.938694	0.3483
@MONTH=10	-6.053834	328.4618	-0.018431	0.9853
@MONTH=11	52.71863	232.7258	0.226527	0.8209
MA(1)	0.906054	0.017504	51.76229	0.0000

R-squared	0.997950	Mean dependent var	96567.22
Adjusted R-squared	0.997904	S.D. dependent var	26324.79
S.E. of regression	1205.300	Akaike info criterion	17.05037
Sum squared resid	8.34E+08	Schwarz criterion	17.15457
Log likelihood	-4998.808	Hannan-Quinn criter.	17.09097
F-statistic	21495.27	Durbin-Watson stat	0.269435
Prob(F-statistic)	0.000000		

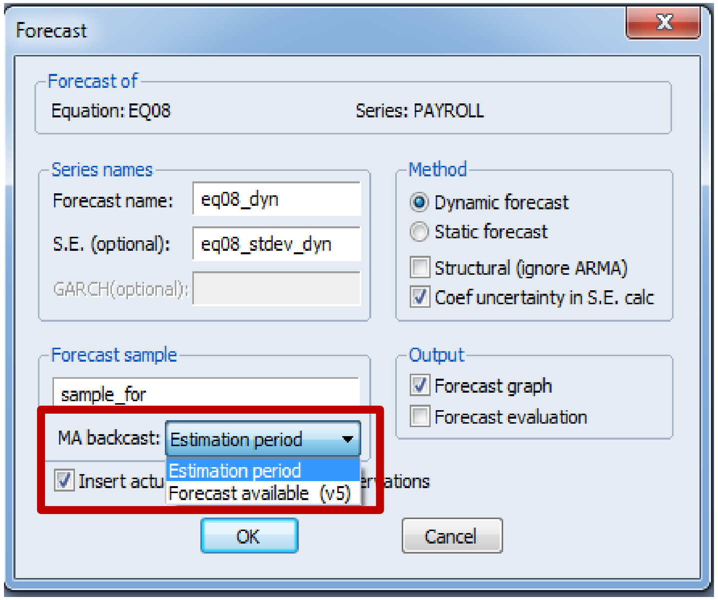
Inverted MA Roots -.91

Forecasting with MA terms: Example 6 (Part II)

- Let’s produce dynamic and static forecast for the MA(1) model.

Example 6: Forecasting with MA terms

1. Open ***eq08*** and click the ***Forecast*** button. As usual, the ***Forecast*** dialog box opens up. Name the series ***eq08_dyn*** and ***eq08_stdev_dyn*** for the dynamic series and ***eq08_stat*** and ***eq08_stdev_stat*** for the static forecast series.
2. Under ***Forecast Sample*** set the sample to ***sample_for*** (see ***Example 3***, ***Part II***).
3. Note that a new field **MA backcast** appears. Here you can choose either of two options: **Estimation period** (the default) and **Forecast available (v5)**. Let’s choose **Estimation period**. Click **OK**.

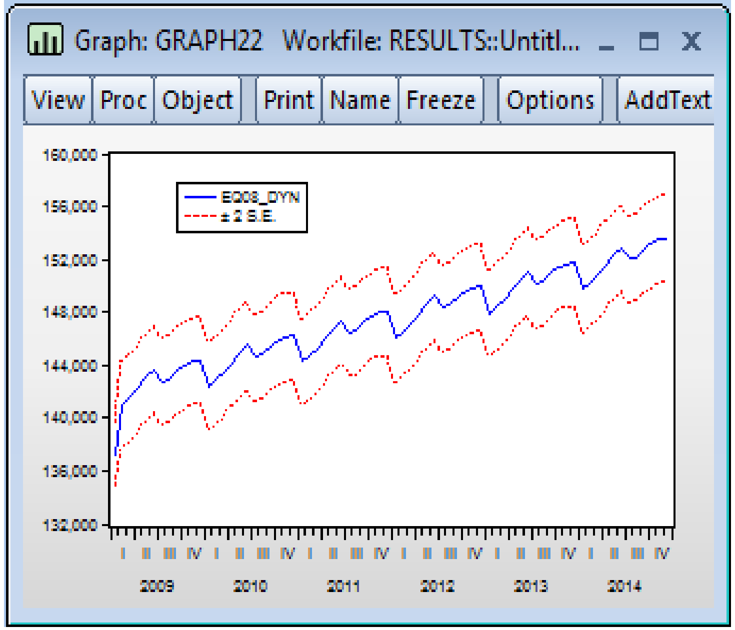


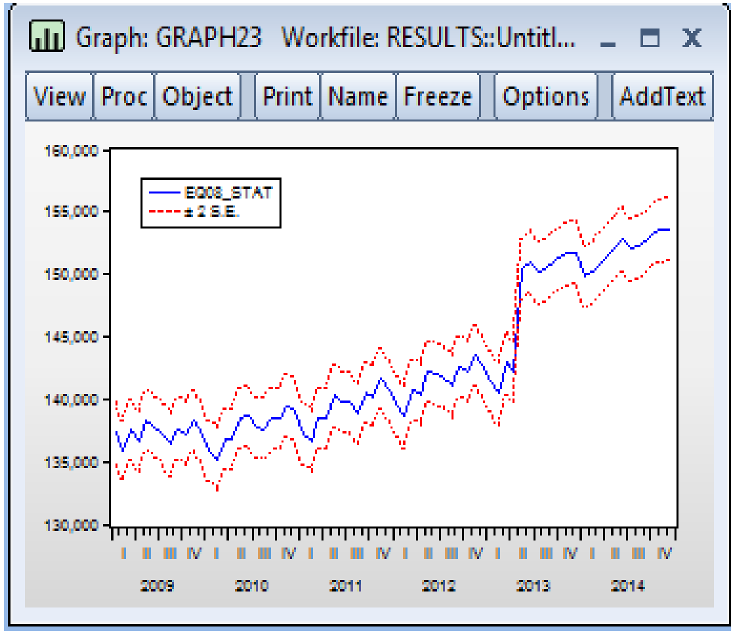
Forecasting with MA terms: Example 6 (Part III) – Technical Notes

- The **Estimation period** method for *MA backcasting* uses data for the estimation sample to compute backcast estimates.
  - ✓ Innovations beyond the estimation sample are set to 0. EViews then uses the unconditional residuals to obtain the pre-estimation sample residuals.
- The **Forecast available (v5)** method for *MA backcasting*, proceeds with different approaches for dynamic and static forecasting.
  - ✓ ***Dynamic forecasting*** – EViews applies the backcasting procedure using data from the beginning of the estimation sample to either the beginning of the forecast period or the end of the estimation sample (whichever comes first).
  - ✓ ***Static forecasting*** – EViews applies the backcasting procedure using data from the beginning of the estimation sample to the end of the forecast period.
- After obtaining the MA backcast estimates of the pre-estimation residuals (using either **Estimation period** or **Forecast available (v5)**), forward recursion is used to obtain values for the pre-forecast sample innovations.
  - ✓ ***Dynamic forecasting*** – We only need to obtain innovation values for the q periods (where q denotes the order of the MA process) prior to the start of the forecast sample. All subsequent innovations are set to 0. In the current example of MA(1) error terms, we need only obtain innovation values 1 period prior to the start of the forecast sample.
  - ✓ ***Static forecasting*** – The forward recursion is carried out through the end of the forecast period.

Forecasting with MA terms: Example 6 (Part IV)

- Because the forward recursion for static forecasts are performed through the end of the forecast period, EViews is able to produce *Static* forecasts that cover the entire forecast sample (*2013m04* to *2014m12*).
- Moreover, beyond *2013m04*, forecasts from *Dynamic* and *Static* model are identical (this is because the forward recursion used to obtain the pre-forecast sample innovations produces same innovations after the end of the historical in *2013m03*).





EViews: Introductory User Guide

BASIC FORECASTING: FORECASTING USING AUTO-SERIES

Forecasting with Auto-Series: Example 7 (Part I)

- One of the most useful features in EViews is the ability to estimate and forecast from equations that are specified using expressions or auto-series.
- Issues with auto-series normally arise when the dependent variable is specified using an expression. In this section we illustrate through a number of examples how EViews performs forecasts in these cases.

Example 7: Auto-Series and Forecasting

1. Type in the command window:

EViews

File Edit Object View Proc Quick Options Add-ins Window

```
smpl sample_est
ls log(payroll) c ip ism tbill3m @trend @expand(@month, @dropfirst)
```

Equation: EQ09 Workfile: RESULTS::Data\

View | Proc | Object | Print | Name | Freeze | Estimate | Forecast | Stats | Resids

Dependent Variable: LOG(PAYROLL)
Method: Least Squares
Date: 05/17/13 Time: 22:45
Sample: 1960M01 2008M12
Included observations: 588

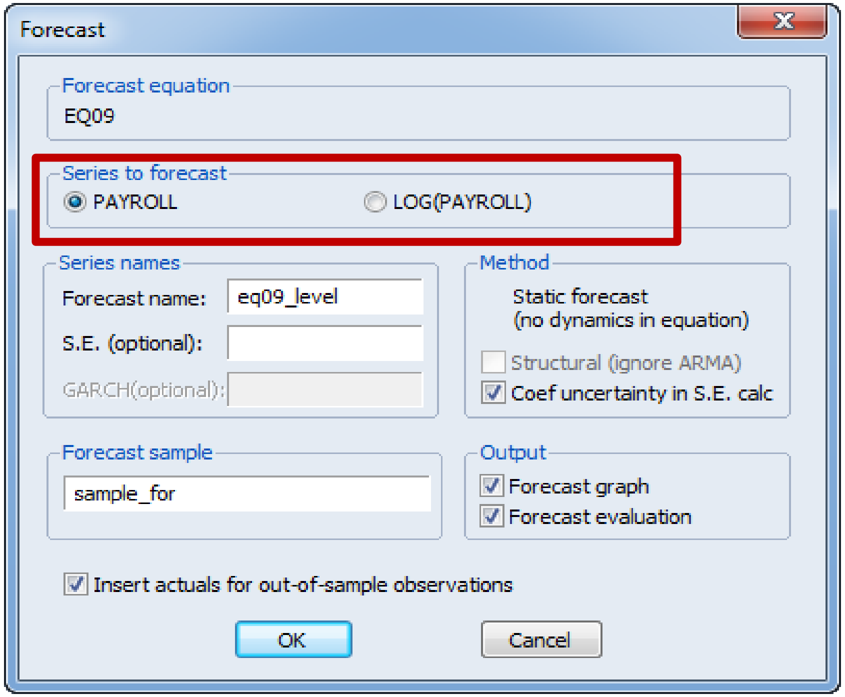
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	10.85320	0.013090	829.0919	0.0000
IP	-0.000617	0.000297	-2.075527	0.0384
ISM	0.000491	0.000191	2.567076	0.0105
TBILL3M	0.010382	0.000470	22.09804	0.0000
@TREND	0.001785	3.94E-05	45.29164	0.0000
@MONTH=2	0.001275	0.005933	0.214923	0.8299
@MONTH=3	0.005878	0.005933	0.990795	0.3222
@MONTH=4	0.013154	0.005933	2.217132	0.0270
@MONTH=5	0.018746	0.005933	3.159434	0.0017
@MONTH=6	0.025001	0.005933	4.213729	0.0000
@MONTH=7	0.013596	0.005933	2.291579	0.0223
@MONTH=8	0.013336	0.005933	2.247903	0.0250
@MONTH=9	0.018946	0.005933	3.193356	0.0015
@MONTH=10	0.022273	0.005933	3.753950	0.0002
@MONTH=11	0.022866	0.005934	3.853503	0.0001
@MONTH=12	0.022652	0.005933	3.817689	0.0001

R-squared	0.989836	Mean dependent var	11.43828
Adjusted R-squared	0.989570	S.D. dependent var	0.287524
S.E. of regression	0.029365	Akaike info criterion	-4.191215
Sum squared resid	0.493227	Schwarz criterion	-4.072120
Log likelihood	1248.217	Hannan-Quinn criter.	-4.144812
F-statistic	3713.721	Durbin-Watson stat	0.035645
Prob(F-statistic)	0.000000		

Forecasting with Auto-Series: Example 7 (Part II)

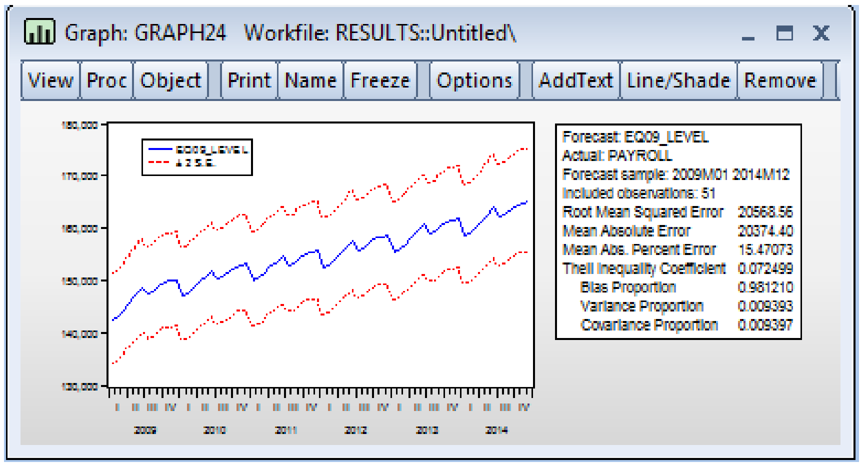
<u>**Example 7: Auto-Series and Forecasting**</u>

1. Click the ***Forecast*** button. As usual, the ***Forecast*** dialog box opens up.
2. Notice here that at the top of the dialog box there is a new section: ***Series to forecast***. Here you can choose to forecast either the underlying series (***payroll***) or the auto-series (***log(payroll)***). Let's do both, first forecasting levels and then logs (we name the level forecast ***eq09_level*** and the log ***eq09_log***).
3. Notice that since this equation does not have a dynamic structure, only the *Static* method is available. Click **OK**.

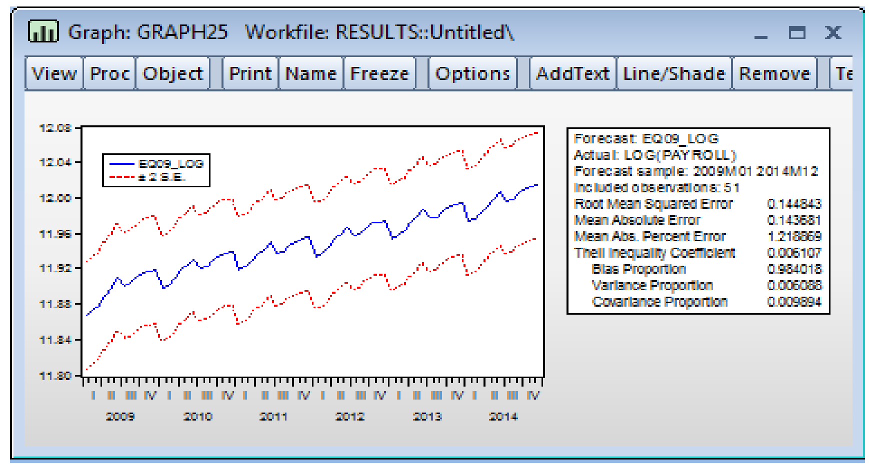


Forecasting with Auto-Series: Example 7 (Part III)

Forecast of Levels



Forecast of Log(Payroll)



Forecasting with Auto-Series: Notes

- If the model includes a lagged dependent variable, it matters for forecasting purposes whether the dependent variable is an auto-series or not.
- One can use more complicated expressions and EViews will be able to forecast the underlying series if is able to normalize the dependent variable expression.
- If the dependent variable is an auto-series derived from two or more series, EViews will offer to provide forecasts of the level of the first series.
- If EViews is unable to normalize the expression for the dependent variable, it will offer to forecast the entire expression (and not the underlying series).

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