Problem Set 2
Econ 40357 Financial Econometrics
University of Notre Dame
Professor Nelson Mark
FALL 2020

1.

2. Let ϵ_t be a white noise error process and consider the following three models that Louie the researcher, says might be a reasonable model of p_t,the logarithm of stock prices

$$p_t = p_{t-1} + \epsilon_t \tag{1}$$
$$p_t = 0.5p_{t-1} + \epsilon_t \tag{2}$$
$$p_t = 0.8\epsilon_{t-1} + \epsilon_t \tag{3}$$

   (a) What class of models are these examples of?

   `ARIMA or ARMA models. (1) is a driftless random walk, or ARIMA(0,1,0).`

   `(2) is an AR(1), and (3) is an MA(1)`

   (b) Compute the first three autocorrelations for each of these models.

   `For (1): (1, 1, 1)`

   `For (2):` $(0.5, 0.5^2, 0.5^3) = (0.5, 0.25, 0.125)$

   `For (3):` $(0.488, 0, 0)$

   (c) From a theoretical perspective, which model is the best candidate for representing stock prices and give a short explanation why.

`Model in (1). Efficient markets hypothesis`

3. Louie the researcher estimates the following model for some returns data

$$r_t = 0.803r_{t-1} + 0.682r_{t-2} + \epsilon_t$$

where ϵ_t is a white noise error process. Is the process stationary? Write a couple of sentences about the implications of whether the process is stationary or not.

`If it's nonstationary, the mean and variance doesn't exist. This creates problems for drawing inference from estimated coefficients, because the distributio theory that we know, only works for stationary time series .`

4. The objective of any econometric modeling exercise is to find the model that most closely 'fits' the data. adding mor lags to an ARMA model will almost always lead to a better fit. Therefore, a large model will be best because it will fit the data more closely. Comment.

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It depends on the purpose of the model.  If it is to describe the dynamics
of the data, then maybe yes, a more extensive model is appropriate.  But
if the objective is to forecast, then no.  The greater the number of estimated
parameters, the greater is the sampling variability impounded into the forecasts,
thus degrading the accuracy of the forecasts
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5. Use the Eviews workfile PS02.wf1, sheet entitled FF_3Factors. Mkt_rf is the monthly market excess return–value-weight return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ that have a CRSP share code of 10 or 11 at the beginning of month t, good shares and price data at the beginning of t, and good return data for t minus the one-month Treasury bill rate (from Ibbotson Associates). For Mkt_rf, estimate an ARMA(2,2). Report the AIC, BIC, and HQIC for each model.

   `Note: the command: mkt_rf c ar(1 to 2) ma(1 to 2) (here). Eviews 'backcasts' the pre-sample observations. mkt_rf c mkt_rf(-1 to -2) ma(1 to 2) gives slightly different estimates.`

6. Open the series mkt_rf. Click proc, automatic ARIMA forecasting. On the options tab, there is a choice of AIC, BIC, and HQIC. For each of these three ICs, run the automatic ARIMA and report the models suggested by AIC, BIC, and HQIC.

7. Estimate an ARMA(2,2) for mkt_rf on observations 1926M07 through 1999M12, then generate static forecasts from 2000M01 through 2019M07. Ask for plots of the forecasts and actuals. Submit the resulting graph that also shows Theil's U2 coefficient.

   Note: what is Theil's U2? In the following, a is the actual.

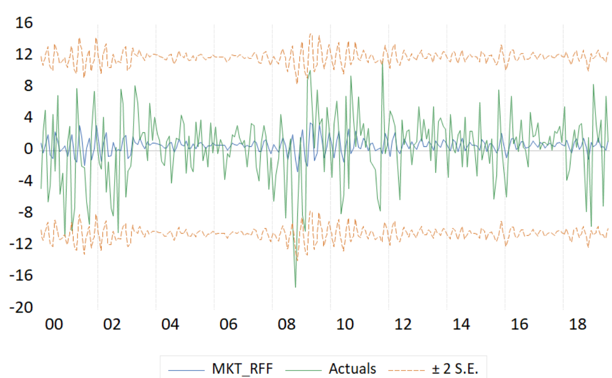
   U2 = sqrt(fpe2/ape2)

   fpe2 = sum (fpe*fpe)

   ape2 = sum (ape*ape)

   fpe = (f(t)-a(t))/a(t-1)

   ape = (a(t-1)-a(t))/a(t-1)



Forecast: MKT_RFF	
Actual: MKT_RF	
Forecast sample: 2000M01 2019M07	
Included observations: 235	
Root Mean Squared Error	4.400178
Mean Absolute Error	3.290306
Mean Abs. Percent Error	129.5090
Theil Inequality Coef.	0.792391
Bias Proportion	0.003097
Variance Proportion	0.609183
Covariance Proportion	0.387720
Theil U2 Coefficient	0.940513
Symmetric MAPE	140.3430

Dependent Variable: MKT_RF
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 09/14/20 Time: 08:36
Sample: 1926M07 2019M07
Included observations: 1117
Convergence achieved after 43 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.662895	0.171489	3.865517	0.0001
AR(1)	−0.275547	0.082315	−3.347455	0.0008
AR(2)	−0.693134	0.048704	−14.23151	0.0000
MA(1)	0.394579	0.079919	4.937268	0.0000
MA(2)	0.743056	0.047696	15.57908	0.0000
SIGMASQ	27.59810	0.631378	43.71087	0.0000

R-squared	0.028394	Mean dependent var	0.662820
Adjusted R-squared	0.024022	S.D. dependent var	5.331988
S.E. of regression	5.267556	Akaike info criterion	6.166454
Sum squared resid	30827.08	Schwarz criterion	6.193411
Log likelihood	−3437.965	Hannan-Quinn criter.	6.176645
F-statistic	6.493634	Durbin-Watson stat	2.019666
Prob(F-statistic)	0.000006		

Inverted AR Roots	-.14+.82i	-.14-.82i
Inverted MA Roots	-.20+.84i	-.20-.84i

Automatic ARIMA Forecasting
Selected dependent variable: MKT_RF
Date: 09/14/20 Time: 08:47
Sample: 1926M07 2019M07
Included observations: 1117
Forecast length: 0

Number of estimated ARMA models: 25
Number of non-converged estimations: 0
Selected ARMA model: (4,4)(0,0)
AIC value: 6.16423432552

Automatic ARIMA Forecasting
Selected dependent variable: MKT_RF
Date: 09/14/20 Time: 08:49
Sample: 1926M07 2019M07
Included observations: 1117
Forecast length: 0

Number of estimated ARMA models: 25
Number of non-converged estimations: 0
Selected ARMA model: (0,1)(0,0)
SIC value: 6.19215386159

Automatic ARIMA Forecasting
Selected dependent variable: MKT_RF
Date: 09/14/20 Time: 08:49
Sample: 1926M07 2019M07
Included observations: 1117
Forecast length: 0

Number of estimated ARMA models: 25
Number of non-converged estimations: 0
Selected ARMA model: (2,2)(0,0)
HQ value: 6.17664461464
